Title

What Affects Millennials' Mobility? PART II: The Impact of Residential Location, Individual Preferences and Lifestyles on Young Adults' Travel Behavior in California

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March 2017

A Research Report from the National Center for Sustainable Transportation

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National Center for Sustainable Transportation

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TABLE OF CONTENTS

What Affects Millennials' Mobility?
PART II: The Impact of Residential Location, Individual Preferences and Lifestyles on Young Adults' Travel Behavior in California

EXECUTIVE SUMMARY

Young adults ("millennials", or members of "Generation Y") are increasingly reported to have different lifestyles and travel behavior from previous generations at the same stage in life. They postpone the time at which they obtain a driver's license, often choose not to own a car, drive less if they own one, and use alternative non-motorized means of transportation more often. Several explanations have been proposed to explain the behaviors of millennials, including their preference for urban locations closer to the vibrant parts of a city, changes in household composition, and the substitution of travel for work and socializing with telecommuting and social media. However, research in this area has been limited by a lack of comprehensive data on the factors affecting millennials' residential location and travel choices (e.g. information about individual attitudes, lifestyles and adoption of shared mobility is not available in the U.S. National Household Travel Survey and most regional household travel surveys).

Improving the understanding of the factors and circumstances behind millennials' mobility is of the utmost importance for scientific research and planning processes. Millennials make up a substantial portion of the population, and their travel and consumer behavior will have large effects on the future demand for travel and goods. Further, millennials are often early adopters of new trends and technologies; therefore, improving the understanding of millennials' choices will increase the ability to understand and predict future trends at large.

This study builds on a large research effort launched by the National Center for Sustainable Transportation to investigate the emerging transportation trends and the impacts of the adoption of new transportation technologies in California, particularly among the younger cohorts, i.e. millennials and the members of the preceding Generation X. During the previous stages of the research, we designed a detailed online survey that we administered in fall 2015 to a sample of 2400 residents of California, including millennials (young adults, 18-34 in 2015) and Gen Xers (35-50 year-old adults). We used a quota sampling approach to recruit respondents from each age group (young millennials, older millennials, young Gen Xers, and older Gen Xers) across all combinations of major geographic region of California and neighborhood type (urban, suburban, and rural).

The result is the *California Millennials Dataset*, a comprehensive dataset that contains information on the respondents' personal attitudes; lifestyles; adoption of online social media and use of information and communication technology (ICT) devices and services; residential

location and living arrangements; commuting and other travel patterns; auto ownership; awareness, adoption and frequency of use of various shared mobility services; major life events in the past three years; expectations for future events; propensity to purchase and use a private vehicle vs. to use other means of travel; political ideas, and sociodemographic traits.

This report summarizes the analyses of the residential location, travel behavior and vehicle ownership of millennials and Gen Xers. In this stage of the research, we augmented the California Millennials Dataset with additional variables measuring land use and built environment characteristics from other sources including the U.S. Environmental Protection Agency's Smart Location Dataset, and the *walkscore*, *bikescore* and *transitscore* from the commercial website walkscore.com. We weighted the data to correct the distribution of cases in the sample, and to reduce the non-representativeness of the data, based on the region of California where the respondents live, the neighborhood type, the age group, gender, student and employment status, household income, race and ethnicity, and presence of children in the household.

We applied data reduction techniques to summarize the information related to the individual attitudes and preferences. To do this, we performed a principal axis factor analysis on the 66 attitudinal variables that were collected in the survey. A total of 17 factors were extracted. Several key differences are observed in the distribution of the factor scores across various groups of millennials and Gen Xers. For example, we find large differences in the attitudinal profiles of millennials and Gen Xers on attitudinal dimensions such as materialism, the propensity to adopt new technologies, and the degree to which individuals feel they are well-established in their life. For other attitudinal factors, e.g. the *pro-environmental policy* attitudes, the differences associated with the location where respondents live are remarkably larger than the differences observed across age groups: urban dwellers consistently report stronger pro-environmental policy attitudes than non-urban residents. We also find that urban millennials are heavy adopters of technology, smartphone apps in particular, and on average use these services more often for various purposes, including accessing information about the means (or combination of means) of transportation to use for a trip, finding information about potential trip destinations (e.g. a café, or a restaurant), or navigating in real time during a trip. Large differences are also observed in the adoption of shared mobility across both age groups and urban vs. non-urban populations; not surprisingly, millennials tend to adopt these technological services more often than Gen Xers, particularly in urban areas.

We further analyzed the relationships between accessibility and the adoption of multiple modes of transportation (*multimodality*, and/or *intermodality*) among the various sub-segments of the population. For this analysis, we classified millennials in two groups of independent and dependent millennials based on their living arrangements and household composition. In fact, the residential location where dependent millennials live has likely been the result of their parents' choices, and not of the millennials themselves. We compared the level of accessibility of the place of residence and the adoption of multimodal travel of these two groups of millennials with those of Gen Xers. Accessibility and multimodality are usually positively correlated: residents of more accessible neighborhoods are more often multimodal travelers. However, millennials, and especially dependent millennials, are found to make the most of their built environment potential, either due to individual choices, or the presence (or lack) of travel constraints. They are less likely to be mono-drivers and more likely to be multimodal commuters, even if they often live in neighborhoods that are less supportive of such behaviors. On the other end of the spectrum, Gen Xers by far rely the most on cars. Independent millennials more often choose to live in accessible locations and tend to adopt non-motorized and multimodal travel options more often.

We estimated a log-linear model of the number of weekly vehicle miles traveled (VMT), using both a pooled model for the entire sample and a segmented model that tests the effects of individual, household and land use characteristics on the VMT of millennials and Gen Xers separately. Interestingly, the model for millennials explains the lowest amount of variance in the data. This finding signals the higher heterogeneity and variation among the members of this group, and the increased difficulty in explaining their behaviors through the estimation of econometric and quantitative models. Traditional built environment variables such as population density and land use mix explain a lower portion of VMT for millennials compared to Gen Xers. Individual attitudes and stage in life (current living arrangements and the presence of children in the household) have larger effects on VMT for millennials than for Gen Xers.

We also investigated the relationships behind car ownership and the type of vehicle owned by a household. Not surprisingly, independent millennials that live in urban areas, on average, own fewer cars per driver than other groups. This finding corroborates the reduced needs for a car in denser (and more accessible) central areas, where a larger portion of independent millennials live. However, such an effect might be short-lived: many older millennials who live in urban areas report that they plan to purchase a new vehicle in the near future. Thus, their zero- or low-vehicle ownership is probably the result of their transient stage of life rather than the long-term effect of preferences towards vehicle ownership. During future stages of the research, we do plan to study how car ownership varies across different groups of the population through the estimation of a model that investigates how sociodemographic characteristics, individual preferences, and land use features affect car ownership. To investigate the preference towards the purchase of various vehicle types among different groups of users, we also estimated a multinomial logit model (MNL) of vehicle type choice, using sociodemographic traits, built environment characteristics, and personal attitudes and preferences as explanatory variables, for the individuals that bought or leased a vehicle that is model year 2010 or newer.

Future stages of the research will focus on the analysis of additional components of millennials' choices, including current residential location, future aspirations to modify vehicle ownership and travel choices, the adoption of shared mobility services, and the relationships between the adoption of shared mobility, household's vehicle ownership, and other components of travel behavior (e.g. the frequency of use of other transportation modes).

Introduction

Young adults (often referred to as "millennials", or members of "Generation Y") are increasingly reported to have different lifestyles and travel behavior from previous generations at the same stage in life. They postpone the time they obtain a driver's license, often choose to live in more central urban locations and choose not to own a car, drive less even if they own one, and use alternative non-motorized means of transportation more often. Several possible explanations have been proposed to explain the observed behaviors of millennials, including their preference for more urban locations, changes in household composition, and substitution of travel for work and socializing with telecommuting and social media.

The behavior of millennials has an important role in explaining the changes in car travel observed in recent years in the United States and other developed countries, where the total vehicle miles traveled (VMT) have, at least temporarily, "peaked" before rebounding sharply, at least in the United States, to new record highs in the first half of 2016 (FHWA, 2016; Circella et al., 2016a). Several studies have started to investigate the factors affecting the residential location and mobility choices of millennials. However, the debate in this field is still dominated by speculations about the potential factors affecting millennials' behavior.

Previous studies have been limited by the lack of information on specific variables (e.g. personal attitudes and preferences, for studies based on National Household Travel Survey data), or the use of convenience samples (e.g. studies on university students). Certainly, the connected tech-savvy millennials are a popular figure in the media headlines, and they are a common presence in San Francisco, Los Angeles, or any other major city in the country. Not all millennials fit this stereotype, though, and there are large masses of young adults that still behave in a way that is more similar to older cohorts: they are likely to get married at a younger age, often live in single-family homes, drive alone for their commute, and raise their children in a predominantly suburban environment. Understanding the different patterns in lifestyles and behaviors among the various segments of the heterogeneous population of millennials, and quantifying their impact on travel demand and the use of various means of transportation, is of extreme importance to researchers, planners and policy-makers.

This study builds on a large research effort launched by the National Center for Sustainable Transportation to investigate the emerging transportation trends and the impacts of the adoption of new transportation technologies in California, in particular among the younger cohorts, i.e. millennials. During the previous stages of the research, a large dataset was collected with a comprehensive online survey that was administered in fall 2015 to a sample of 2400 residents of California, including both millennials (young adults, 18-34 in 2015) and members of the preceding Generation X (middle-age adults, 35-50). We used a quota sampling process to ensure that enough respondents from all age groups (*young millennials*, *older millennials*, *young Gen Xers*, and *older Gen Xers*) were sampled from each combination of geographic region of California and neighborhood type (urban, suburban, and rural), and controlled for demographic targets of the sample for five dimensions: gender, age, household income, race and ethnicity, and presence of children in the household.

The result is the California Millennials Dataset, an unprecedented dataset which contains detailed information on the respondents' personal attitudes, preferences and environmental concerns; lifestyles; adoption of online social media and use of information and communication technology (ICT) devices and services; residential location and living arrangements; commuting and other travel-related patterns; auto ownership; awareness, adoption and frequency of use of the most common shared mobility services (including car-sharing, bike-sharing, dynamic ridesharing and on-demand ride services such as Uber or Lyft); major life events happened in the past three years; expectations for future events and propensity to purchase and use a private vehicle vs. to use other means of travel; political ideas and sociodemographic traits.

During this stage of the research, we built on the California Millennials Dataset, integrated the dataset with additional data available from other sources, and investigated several topics related to millennials' mobility choices and the changing trends in travel demand in California. Specifically, as part of the study, we geocoded the residential location and the primary work/study location reported by each respondent in the sample. Using also the information from the geocoded residential and work locations of the respondents, we developed a set of quality checks, and further cleaned and recoded the information available in the dataset. We matched the respondents' geocoded residential location with the information on the dominant neighborhood type available from another research project developed at UC Davis. Further, we developed a set of weights, using both cell weights and the iterative proportional fitting (IPF) raking process, to correct for the non-representativeness of the sample in terms of distribution by region of California, predominant neighborhood type, age group, gender, household income, student and employment status, race and ethnicity, and presence of children in the household.

Based on the geocoded residential location of the respondents, we integrated the dataset with additional variables obtained from external sources. The additional variables provided information on the characteristics of the built environment in the place of residence and travel accessibility by mode, from multiple sources including the U.S. Environmental Protection Agency (EPA) Smart Location Dataset, and the commercial website Walkscore.com (which also computes a *bike score* and *transit score*, in addition to the better-known *walk score*). We applied factor analysis as a data reduction technique to investigate the relationships relating the 66 attitudinal variables available in the dataset and to extract 17 factors that measure attitudinal constructs on several dimensions of interest. We developed a number of analyses using the information in the dataset, focusing in particular on the impacts of land use characteristics and the different behaviors observed, for example, among "urban" millennials vs. the other groups of young adults who live in suburban or rural areas, and the corresponding groups of Gen Xers. This report summarizes the findings from this stage of the research.

In the remainder of this report, we first discuss recent studies that have investigated several aspects of millennials' mobility and car ownership choices. We then present the information contained in the *California Millennials Dataset*, summarize the data cleaning and recoding tasks that were performed as part of this stage of the research, describe the process that was used to geocode the residential and work locations of the respondents, the weighting process applied to the dataset, and the additional data that were imported from external sources and that were matched based on the geocoded residential location of the respondents, and present how we applied factor analysis on the 66 attitudinal statements in the dataset to extract 17 main attitudinal factors. The following sections investigate differences among millennials and the members of the Generation X that live in urban, suburban and rural areas, starting from the use of social media and smartphone apps to coordinate travel alternatives and to access information on the means of transportation available for a trip, information about potential trip destinations and real-time travel information, among others, and then moving to discuss the different attitudinal patterns reported by the residents of various neighborhood types, by generation. We present several measures of accessibility and investigate the adoption of multimodal travel among different groups segmented by generation and neighborhood type. The following chapter presents a set of econometric models of the individuals' vehicle miles traveled (VMT), which were estimated as both a pooled model (for the entire sample) and segmented models for millennials and Gen Xers. The models allow identifying the impacts of individual and household characteristics, stage in life, land use characteristics, adoption of technology and personal attitudes on the amount of car travel of millennials and Gen Xers. We then turn our attention to car ownership and vehicle type choice, through the comparison of the different car ownership levels found among members of different generational groups that live in the various neighborhood types. We estimate a discrete choice model of the vehicle type choice, which sheds light on the impact of several groups of explanatory variables on the decision to buy or lease a specific type of vehicles, and discuss the different trends in the propensity to change the level of vehicle ownership in the household (e.g. propensity to buy a new vehicle) observed among the members of different generational groups that live in urban vs. non-urban locations. The final conclusions summarize the findings from this stage of the project, and identify directions for future research. The activities developed so far in this research project and the large amount of information that has been collected will allow a number of additional analyses of potential interest for the research community, planners and policy-makers; these will be developed during the next stages of this multi-year research program.

This Part II Report builds on the Part I Report titled "What Affects Millennials' Mobility? PART I: Investigating the Environmental Concerns, Lifestyles, Mobility-Related Attitudes and Adoption of Technology of Young Adults in California", which provided detailed information on the motivations for this study, previous studies from the literature on which this research builds, the data collection effort, the content of the online survey that was used in the study, the sampling methodology and preliminary analysis of the California Millennials Dataset. Additional information on these topics can be found in the Part I project report (see Circella et al., 2016b).

The Mobility of Millennials

Millennials (i.e. the young adults born in the 1980s and 1990s, who became adults in the 21st century) are often reported to behave differently from previous generations at the same stage in life. Several studies have discussed the changing trends in millennials' lifestyles and mobility decisions. Millennials are found to postpone the time they obtain a driver's license, often choose to live in more central urban locations and choose not to own a car, drive less even if they own one, and use alternative non-motorized means of transportation more often (Blumenberg et al. 2012; Kuhnimhof et al. 2012; Blumenberg et al. 2015; McDonald 2015; Circella et al. 2016b). Several possible explanations have been proposed to explain the observed behaviors of millennials, including their preference for more urban locations closer to the vibrant parts of a city, changes in household composition, and the substitution of travel for work and socializing with telecommuting and social media.

In this study, we follow the definition of "millennials" that is consistent with the recent studies published by the Pew Research Center, which identify millennials as the individuals born between 1981 and 1997 (i.e. they were 18 to 34-year-old, as of 2015). This segment of the population may have different behaviors and lifestyles from older generations, even while controlling for stage of life, causing them to travel differently. Several studies have started to investigate the changing trends in millennials' mobility, and the factors that are likely to affect their choices. For an extensive review of the literature that has focused on millennials' behavior, please refer to the Part I report from this project (Circella et al., 2016b).

It is difficult to separate the generational component of millennials' behaviors from other factors affecting their mobility choices, including the changing economic conditions and fluctuations in fuel prices, traffic congestion in large metropolitan areas, changes in the urban form of American cities, household composition and personal lifestyles, the eventual substitution of physical trips with information and communication technologies (ICT), a stronger tendency towards multimodality, and the increased availability of alternative travel options including new shared mobility services such as car-sharing and on-demand ride services (e.g. those provided by transportation networks companies, or TNCs, such as Uber or Lyft, in the American market) (Wachs, 2013, Polzin et al., 2014; Buehler and Hamre, 2014). Recent sociodemographic shifts and modifications in habits and lifestyles include modifications in household composition, living arrangements, changes in personal attitudes, reduction in (and postponement of) childbearing, and the increased diversity in the population (Zmud et al., 2014). The increased diversity of the population, in particular, may contribute to decreasing the average VMT per capita of younger generations: Blumenberg and Smart (2014) found that (similarly to other studies) immigrants are more likely to carpool than those born in the United States, even if large differences exist depending on the origin of the individuals and the place where they were raised. Blumenberg and Smart (2014) analyzed 2000 census data and 2001 travel survey data, and found that the percentage of foreign-born in a census tract is positively correlated with carpooling rates. Shin (2016) examined ethnic enclaves in the 2012-2013 California Household Travel Survey, and found similar results. Specifically, the author found that immigrants residing in ethnic enclaves have higher rates of household-external carpooling for non-work trip purposes than immigrants residing outside ethnic enclaves. The study postulates that ethnic enclaves may offer stronger social networks, which may affect mode choice (Shin 2016).

Millennials' behavior differs from that of their older counterparts due to a complex combination of lifecycle, period and cohort effects, including lifestyle-related demographic changes, such as shifts in employment rates, delays in marriage and childbearing (Pew Research Center 2014), and shifts in attitudes and use of virtual mobility, which are believed to be more specific of their cohort (as suggested by McDonald, 2015). In their analysis of National Household Travel Survey (NHTS) data, Polzin et al. (2014) showed that millennials exhibit different travel behavior than the previous generations at the same age – specifically, 20-34 year olds in 2001 drove more miles per year than 20-34 year old in 2009- and identified several factors such as residential location, race, employment and economic status, living arrangements, licensure status, among others, that are expected to influence millennials' mobility. McDonald (2015) also analyzed NHTS data and highlighted that all Americans traveled less from 1995 to 2009, but millennial travel decreased the most. The study indicated that demographic shifts typical of the 18 to 34 age group could explain 10-25% of differences observed in travel patterns. The author concluded that an additional portion (35-50%) could be explained by other variables such as changing attitudes or virtual mobility, even if she could only infer this as NHTS data do not contain information on these variables. The remaining percentage is attributed to the general decline in travel across all generations (McDonald 2015).

Modern technological innovations further contribute to reshaping transportation. The adoption of ICT, e.g. online shopping, telecommuting, etc., is attributed an important role in reshaping individuals' relationships with the use of travel modes and organization of activities (cf. Mokhtarian, 2009; Circella and Mokhtarian, 2017; Circella et al., 2016a). Shared mobility services have further reshaped transportation through the introduction of options that give users increased mobility and accessibility without incurring the costs of owning a vehicle. Shared mobility services range from car-sharing services, including fleet-based services such as Zipcar or Car2Go and peer-to-peer services such as Turo, to ridesharing services, including dynamic carpooling such as Carma and on-demand ride services (also known as ridesourcing) such as Uber and Lyft, and bike-sharing services. Shared mobility services modify a number of key factors related to travel decisions, including travel cost, convenience and security (Taylor et al. 2015). The adoption of these services can affect the level of auto ownership of a household, and contribute to shifting individuals' preference away from car ownership with potential sizable impacts on daily schedules, lifestyles, and even residential location. Not surprisingly, early adopters of shared mobility services are predominantly well-educated young individuals who live in urban areas (Rayle et al. 2014; Taylor et al., 2015; Buck et al.; 2013). These services are particularly popular among millennials, who are heavy users of ICT devices and are more open to the sharing economy (Polzin et al., 2014; Zipcar 2013; Buck et al., 2013; Rayle et al., 2014).

There is continued interest in investigating millennials' travel patterns (and the reasons behind the observed differences with their older counterparts), also in consideration of the large size of this segment of the population, and the likely large effects that their choices will have on future consumer expenditures, demand for housing, and travel demand. In a recent analysis of 1990, 2001, and 2009 NHTS data, Blumenberg et al. (2016) found that there was a significant drop in driving (Personal Kilometers Traveled - PKT) in the 2000s. They examined numerous factors including drivers' licensure, employment, web use, and transitions to adulthood, including a number of variables to describe stage of life, such as living with parents, etc. The authors found no statistical relationship among the majority of these variables and PKT. However, and not surprisingly, employment was consistently and positively associated with PKT. They concluded that declining employment during the Great Recession contributed significantly to the decline in youth travel between 2001 and 2009 (Blumenberg et al. 2016). During that time, unemployment more than doubled. The authors found that the effect of employment was 32% greater among older (ages 27–61) than younger (ages 20–26) adults. They interpreted these results to suggest that economic factors were at the root of the decline in personal travel in the U.S. during the 2000s.

Garikapati et al. (2016) analyzed older and younger millennials, and found that older millennials are becoming increasingly like their Gen X counterparts at a similar age. However, it is unclear if millennials will adapt to the same travel patterns of the prior generations or if lingering differences will remain in their travel and time use patterns. The issue has important planning implications. For example, real estate sales data signal an increase in the number of millennials moving to more suburban developments, even if with a "delay effect" associated with the later time in which members of these generations establish new households. If such a trend expands in future years, with an increase in suburban living, it is likely to bring important consequences in terms not only of the demand for housing, but also of future travel demand, and the use of various transportation modes. On the other hand, the reported preferences of millennials for urban lifestyles has been prompting hopes for a further increase in the popularity of central urban neighborhoods, which have already gone through a process of progressive renewal and regeneration during recent years (Wachs, 2013). Millennials, with their lower per-capita VMT and auto ownership are credited by many as important actors that can help planning agencies and regulators reach the milestones of reduction in VMT and GHG emissions from transportation often included as part of planning processes also as the result of environmental regulations (as in the case of the Sustainable Community Strategies mandated in California by the Senate Bill 375 and related regulations). This goal is also mirrored in the changes happening in the real estate trends, and changing regulations in many jurisdictions, for example through the revision of parking requirements for new developments and changes in zoning regulations. Further, millennials are more likely to live in multi-generational households than previous generations at the same age, with additional implications in terms of their access to private vehicles owned by a household, and coordination of travel patterns with other household members. Fry and Passel (2014) found that by 2012, 24% of young adults lived in multi-generational households, up from 19% in 2007, and 11% in 1980. This share is higher among men (26% of male 25-34 year olds live in multi-generational households, compared to 21% of women). The authors conclude that this may be a manifestation of the delayed entry to adulthood (along with later marriage and childbearing) (Fry & Passel 2014), which are all factors associated with potential impacts on individual travel behavior (i.e. due to the delayed lifecycle effects).

In a study of Australian driver's licensing trends, Delbosc and Currie (2014) concluded that full-time employment and the presence of children in the household were strong predictors of licensing status, with higher licensing rates among young adults who work full-time (in particular if they have children), compared to part-time workers and students. They posit that changes in living arrangements and state of life may cause reduced or postponed licensure of young adults (Delbosc & Currie 2014). The same seems to be true for car ownership: in an examination of millennial car ownership, Klein and Smart (2017) used eight waves of data from the Panel Study of Income Dynamics. They found, consistent with previous literature, that young adults own fewer cars than previous generations at the same life stage. In particular, the authors found that economically *independent* young adults (i.e. those that have already established their own household) own more cars than expected for their income and personal wealth, therefore positing that economic factors are the main ones limiting youth car ownership. As young adults become economically independent from their parents, their car ownership rates tend to increase. This conclusions seems to imply that recently observed "peak car" trend may reverse in future years, the more the economy recovers and more millennials "leave the nest" (Klein & Smart, 2017).

Younger generations may prefer multimodal mobility, as well. Vij et al. (2015) used cross-sectional travel diary data from individuals in the San Francisco Bay Area in 2000 and 2012 to develop a latent class model of travel mode choice behavior. Their findings indicate shifts in the region towards greater multimodality. During the observed period, motorized vehicle mode shares decreased from 85% in 2000 to 81%, while the proportion of the population that only considers private vehicle when deciding how to travel declined from 42% to 23%. The authors of the study concluded that changes in economic and social factors and level of service of different travel modes had a marginal effect, but did not account for the entire decline in vehicle mode shares observed from 2000 to 2012. Further, they found that the modal shifts exist across the entire population, and were not limited to any one generation (Vij et al. 2015).

Many of the topics mentioned above are investigated as part of this study. Understanding the factors affecting millennials' choices, and their potential long-term impacts on travel demand, is extremely important to planning processes and policy-making. Still, previous studies have been limited by either (1) the lack of information on specific variables, such as personal attitudes or the adoption of new technologies and emerging mobility services, for studies based on NHTS or other household travel surveys at the statewide or metropolitan planning organization (MPO) level; or (2) the use of non-random samples, such as convenience samples drawn from specific segments of the population, e.g. university students. This study has been designed with the aim of overcoming some of these limitations.

The California Millennials' Dataset

This study builds on a large research effort undertaken to investigate the relationships among millennials' residential location, individual attitudes, lifestyles, travel behavior and vehicle ownership, the adoption of shared mobility services, and the aspiration to purchase and use a vehicle vs. use other means of transportation in California, which was designed to overcome some of the limitations from previous studies. During the previous stage of this project, which was also primarily funded by the National Center for Sustainable California and Caltrans, a rich dataset was collected in fall 2015 with a comprehensive online survey that was administered to a sample of 2400 California residents, including millennials (i.e. young adults, 18-34, in 2015) and members of the preceding Generation X (i.e. middle-age adults, 35-50). We used a quota sampling approach to recruit respondents from each of the six major regions of California and three dominant neighborhood types (urban, suburban and rural), while controlling for sociodemographic targets including household income, gender, race and ethnicity, and presence of children in the household.

The result is the California Millennials Dataset, an unprecedented dataset which contains information on the respondents' personal attitudes and preferences, lifestyles, adoption of online social media and information and communication technology (ICT), residential location, living arrangements, commuting and other travel-related patterns, auto ownership, awareness, adoption and frequency of use of the most common shared mobility services (including car-sharing, bike-sharing, dynamic ridesharing and on-demand ride services such as Uber or Lyft), propensity to purchase and use a private vehicles vs. use other means of travel, major life events that have happened in the past three years and that might have influenced the current lifestyles, residential location and travel behavior, environmental concerns, political ideas and sociodemographic traits. The analysis of the rich amount of data contained in this dataset allows us to address a number of research questions that have received attention in recent years in the scientific and planning community. The remainder of this section provides summary information on the California Millennials Dataset, and on data handling, cleaning and transformation that were carried out to expand and integrate the dataset with additional information available from other data sources, in order to develop the analysis of interest for this research. For more detailed information on the survey content, data collection effort and sampling strategy behind the creation of the California Millennials Dataset, please refer to the Part I project report (Circella et al., 2016b).

The data collection process was specifically designed to investigate the relationships associated with the behavioral processes and mobility-related decisions of young adults (millennials), and to investigate the impact that several groups of variables, including changes in lifestyles, sociodemographic trends and the adoption of emerging mobility services, have on the travel decision this dynamic segment of the population. In addition, the presence of a *control group* composed of members of the older Generation X is useful to allow comparisons across generations in the study, using the same methodologies for data collection and selection of respondents for the entire sample.

The survey used to collect the original information included in the California Millennials Dataset includes 11 sections, which collected information on variables relevant for the analysis of millennials' mobility and other emerging transportation trends:

a. *Individual attitudes and preferences*, measured through the agreement with a group of 66 statements on a five-level Likert scale, for 20 dimensions including social habits, lifestyles, adoption of technology, environmental concerns, exercise/physical activity, individualism, materialism, time organization, etc.;
b. *Use of online social media (Facebook, Twitter, among others), and adoption of ICT devices and services*, e.g. frequency of use of smartphone apps to book transportation services, purchase tickets, check traffic conditions, or decide what mode of transportation to use; ownership and regular use of various ICT devices; adoption and frequency of use of e-shopping;
c. *Residential location and living arrangements*, including the self-reported characteristics of the neighborhood where the respondents live, detailed address (or closest two-street intersection near the home address), information about tenancy, years the respondent has lived at that addressed, and information about the other people who live with the respondents (e.g. partner, parents, children/grandchildren, siblings or other relatives, eventual roommates/flatmates, etc.);
d. *Employment and work/study activities*, including detailed information about occupation, type of job(s), field of occupation, student status, work schedule, number of hours worked in the average week for the main occupation and for any volunteering activities;
e. *Transportation mode perceptions*, including perceptions of driving, public transportation and active modes (walking, biking). These perceptions include comfort, reliability, safety, cost, privacy, and ability to multitask while using these modes of transportation, among others;
f. *Current travel choices*, including detailed information on the typical usage of various means of transportation (private vehicle, carpool, shuttle, public transportation, bike, etc.) for both commutes and leisure trips. This section also collected information on the self-reported commute distance and average time spent commuting, the location of main commute destination (work or school), the activities conducted while traveling, and the respondent's long distance travel patterns (measured in terms of the number of long distance trips made by different travel modes for either business or leisure purposes, during the previous 12 months).
g. *Awareness, adoption and frequency of use of the most common shared mobility services* (including car-sharing, bike-sharing, dynamic ridesharing and on-demand ride services such as Uber or Lyft); the section collected information about the shared mobility services that are available where the respondent lives (e.g. peer-to-peer car-sharing such as Turo, fleet-based car-sharing such as Zipcar, on-demand ride services such as Uber or Lyft, etc.) and how often the respondent uses these services. We also collected information on why the respondent used Uber/Lyft, how this impacted their alternative

mode choice, e.g. the decision on whether to use public transportation, or chose not to drive, and what eventually limits or prevents the use of on-demand ride services.

h. *Driver's licensing status and vehicle ownership*, including information on whether a respondent has a drivers' license, the type of license they have, and the legal age to obtain a license in the place where the respondent grew up. This section also includes questions on the percent of time a car (and/or motorcycle) is available to the individual, the number of vehicles owner by the individual's household, and detailed information (year, make and model) of the vehicle that is used most often. This section included detailed questions on the factors behind the respondents' decision to purchase the vehicle (used or new). Finally, this section collected information on the number of miles a respondent travels per week by car and by bike, the type of parking available at the place of residence (if any), and if the respondent has a public transportation pass.
i. *Previous travel behavior and residential location* (and information on the major life events from the past three years): this section collected information about the life events from the past three years (e.g. moving to a new city or state, buying a home, beginning study, moving in with a partner, having children, etc.). This section also collected information on why a participant may have moved and the impact of several factors on this choice (e.g. birth of a child, quality of the school district, housing price, parking availability, ease of walking and biking etc.). This section also collected information on how much participants travel by each mode now compared to three years ago.
j. *Expectations for future events* (and propensity to purchase and use a private vehicle vs. to use other means of travel), including if the participants expects/plans to move, and/or foresee changes in the household composition in their jobs or school they attend. This includes data on how participants expect to travel in three years from now, compared to how they currently travel, by mode. Finally, the section collected information on the interest in purchasing a new vehicle (and the type of vehicle they would consider purchasing or leasing) and/or in joining or leaving a car-sharing program.
k. *Sociodemographic traits*, including gender, age, US state or foreign country where the individual was raised, political views, household size and composition, individual and household income, education level, parents' education, and number of drivers in the household.

During the survey design, we engaged several stakeholders and worked with colleagues at other research institutions, California state and local agencies, and other partner organizations, to obtain feedback on the survey content and improve the survey tool. We extensively pretested the survey, and tried to balance the trade-off between the complexity of the content of the survey (and the amount of information that is collected) and the time required to complete the survey.

We administered the survey to a sample of millennials and members of Generation X in California. We used a web-based opinion panel to invite members of these segments to complete the survey, and used a quota sampling approach to ensure that enough responses were included from each geographic region of California and neighborhood type where the respondent lives (classified in predominantly urban, suburban and rural areas). Sociodemographic targets were used to make sure that the sample mirrored the characteristics of the California population on five key sociodemographic dimensions: sex, age, income, race and ethnicity, and presence of children in the household. For the purposes of this study, we divided California in six major regions:

- MTC – Metropolitan Planning Organization (San Francisco Bay Area);
- SACOG – Sacramento Area Council of Governments (Sacramento region);
- SCAG – Southern California Council of Governments (Los Angeles/Southern California);
- SANDAG - San Diego Association of Governments (San Diego);
- Central Valley (eight counties in the central San Joaquin Valley); and
- Northern California and Others (rest of state not included in the previous regions).

A total of 5,466 invitations were sent out, and 3,018 complete cases were collected. The high response rate of 46.3% is not surprising considering the data collection method used for this project, and the higher propensity of opinion panel members to respond to survey invitations. After excluding severely incomplete, inconsistent or unreliable cases, a final dataset that included approximately 2,400 valid cases was used to compute initial descriptive statistics and other analyses reported in the Part I report (Circella et al., 2016b).

While the sampling method used to recruit the participants for this study (based on the use of an online opinion panel) and the use of an online survey might represent a potential source of bias for the research, and caution should be used in generalizing the results from the study to the entire population of California, the use of the same methodology for the recruitment of both members of the millennial generation and of the preceding generation X ensures internal consistency in the collection of the data and creation of the dataset. In other terms, if any sampling and response biases affect the study, it is reasonable to expect that the similar biases affect both the millennials and Generation X subsamples. For this reasons, even if eventual biases are present in the data collection and sampling approach used for the research, the comparisons between the observed behaviors, and relationships, between millennials and Gen Xers presented in this report remain valid.

The data collection effort was designed as the first step of a longitudinal study of the emerging transportation trends in California, designed with a rotating panel structure, with additional waves of data collection planned in future years. The research team is currently working with the funding agency, in order to define the plan for the future components of the longitudinal (panel) study, also through the integration of the information collected with this survey with additional travel diaries and travel data collected with GPS-based smartphone apps. Further, in future stages of the research, we plan to expand the data collection also through other channels, also through the creation of a paper version of the survey, in order to expand the target population for the study, and reach specific segments of the population, e.g. elderly or people that are not familiar with the use of technology or who do not have easy access to the internet and would not likely complete an online survey. Also, we are considering creating a version of the survey in Spanish, in order to better reach the California population of Latinos and increase the response rate among the Hispanic minority.

Data Cleaning and Recodes

In order to enforce strict quality control in the collection of respondents, we devised several measures to identify and remove problematic or inconsistent cases from the dataset. Among the strategies that were developed for purposes of quality assurance, we used a common quality assurance practice in the form of two to three "trap" questions (depending on the version of the survey that was administered to the respondent) that were included in various sections of the survey. Further details about the trap questions that were used and the strategies that were used to identify inconsistencies in the dataset can be found in the Part I project report (Circella et al. 2016b).

In addition to the use of trap questions, we checked the consistency of responses throughout the survey through the application of several criteria. The consistency checks that were used also included verifying the speed with which respondents answered the survey. For example, we removed individuals who failed a trap question and also completed the survey in a very short time (below 20 minutes) as a sign of lack of attention during the completion of the survey. The average response time for this survey was approximately 35 minutes. Therefore, it would have been extremely difficult to complete the survey in less than 20 minutes.

Additional criteria that were used during the process of data cleaning and recoding are discussed in the sub-sections below. These criteria included checking internal consistency of a case, analyzing survey response outliers, and inconsistencies between the information reported by the respondent in the main body of the survey and in the screener from the opinion panel.[1]

Internal consistency

As part of the internal consistency checks, we identified and carefully reviewed cases that were considered suspicious according to one or more of the following criteria:

- *Flatliners:* Individuals who "flatlined" one or more sections that had conflicting statements (e.g. respondents who answered yes to both statements: "I expect to move in the next three years" and "I expect to stay in my current house in the next three years.")
- *Locational consistency:* For example, individuals who provided the same address for work and home, though they indicated that they did not telecommute, or individuals who perceived neighborhood type as extremely different from the objective measures that were determined using geocoded values for the home address.

[1] The opinion panel used a short screener, which contained only nine questions, to recruit and select participants for the study.

- *Travel pattern:* We assessed mode availability for commute and leisure trips according to the reported location, trip distance and time of the commuting trips, and through the comparison of the geolocated work and home addresses. We also evaluated the cases that reported frequent use of multiple modes, and inconsistency in the reported multi-tasking activities during the most recent commute trip.
- *Use of emerging transportation:* Respondents who reported that they used services that are not available in the areas where they live (the survey explicitly asked respondents whether they used the service in their home town or while traveling away from home), or respondents who reported that they used multiple services with very high (and unrealistic) frequency over short periods of time (e.g. respondent that used Zimride, Turo, Zipcar and Uber very frequently, especially if located in locations where these services are not largely available).
- *Household composition*: Several questions in the survey asked information related to the household composition and living arrangement, allowing the researchers to establish whether the reported number of children and number of adults in the household, and their age ranges, are consistent with the information reported about the other individuals that live in the household (in the previous section C of the survey)

Cases that failed one or more criteria listed above were, in most cases, removed from the dataset, unless some valid reasons for the internal consistency were identified.

Response outlier

We reviewed cases that pose problems related to one or more of the following criteria:

- *Daily activity patterns*: individuals who report activities that are implausible or impossible (e.g. watching TV for 24 hours in one day).
- *Long distance trips*: Individuals who reported extremely high number of long distance trips for either business or leisure trips (over 100 miles).
- *Money spent on Uber/Lyft*: Individuals who report spending very high monthly amount of money on Uber compared to the self-reported frequency of this service.
- *Number of cars*: Respondents who report very high or very low number of cars compared to their household size and structure and the reported commute pattern (e.g. individuals that report that they travel driving alone in a car on a daily basis, but then report that they live in a zero-vehicle household).
- *Vehicle miles traveled*: Individuals who reported illogical average weekly VMT for commutes and travel patterns (e.g. individuals that likely reported annual VMT, by mistake, instead of the weekly VMT, or that reported zero VMT, but then reported that they drive alone to work/school in their commute pattern).

The information associated with the cases identified through one of criteria above was either removed from the dataset, or recoded accordingly (e.g. some variable values were recoded to "missing"), depending on the severity of the problems that were identified.

Inconsistency between the Survey and Screener Questions

We also identified inconsistencies between the information reported in the survey and the information that was reported when answering the questions that were proposed in the screener used by the online survey company to pre-screen respondents during the recruitment of participants for the study. We designed the screener to ensure that a sample that is as representative as possible of the population in the state of California could be assembled for this study. The screener collected information on the following variables: gender, age group, Hispanic origin, race, household income, Zip code of the place of residence, neighborhood type, presence of children in the household, and number of children in the household. In particular, we checked the consistency for the following variables:

- *Gender:* we compared the screener data with the survey data.
- *Age group*: There were several cases for which the age was not consistent with the reported groups: in this case we checked the screener age groups with the survey response.
- *Neighborhood type*: We compared the perceived and geocoded measures of neighborhood type (suburban, urban, rural) and individual reviewed cases that had differences in the reported neighborhood type, to identify the reasons for the different information.
- *Presence of Children*: We assessed the presence of children in the home given the responses in section C and section K of the survey, and compared them to the information provided in the screener.

In most cases, the inconsistencies above led to recoding the screener data, given that the survey information was considered more accurate, e.g. the screener can sometimes be filled by other members of the household. However, cases with more severe inconsistencies were removed from the sample. We recoded some responses on a case by case basis, reviewing all answers provided by a respondent. In some situations, we recoded a variable to “missing” value, when the information about that variable could not be assessed with certainty. In the case of the screener inconsistencies we recoded either the survey or the screener depending on the case.

A list of recodes was prepared and implemented in the final dataset. After assessing the cases which presented some inconsistencies or other reasons for not being considered reliable, we retained 2155 cases in the dataset used for the analyses in this report, from the more than 3000 cases that were originally collected (and approximately 2400 cases that were used for the initial analyses in the Part I report).

Geocoding

To make the California Millennials Dataset rich with various information from external data sources, we first geocoded the residential, school, and workplace addresses of individual respondents by employing one of the reliable geocoding methods, the Google Maps application programming interface (API). Other geocoding methods were also considered, including the ESRI Desktop ArcGIS geocoding toolbox and the ESRI ArcGIS online geocoding tool. These tools were tested and used in initial components of the geocoding process. However, they were not used in the final geocoding process, because of some limitations that made them not well suited for this project. In particular, the Desktop ArcGIS toolbox needs a street network in a specific form as an input for geocoding, and most users use the US Census topologically integrated geographical encoding and referencing (TIGER) Address Range-Feature shapefile as the input. Although the US Census have regularly updated this shapefile, it is far from being perfect. For example, the first and last street numbers of street segments in this file are often not recently updated. Moreover, because ArcGIS is not a search engine such as Google and Bing, if addresses are misspelled, its geocoding outcomes are not as good as those from online search engines that often successfully find full addresses also in case of partial ones based on previous searches and selections from other users. This property also comes with some disadvantages, though, as the Google Maps API might sometimes return wrong addresses as the result of the predictions of their search engine. Still, in this project, it was found to be preferable to use the Google Maps API, with some additional quality checks that were performed by the research team as a post-process, to verify that the address geocoded by Google reasonably matched the original address provided by the user. As for the ArcGIS online, although ESRI claims that its geocoding outcomes are more accurate than those obtained by employing the US Census shapefiles, ESRI did not explicitly reveal the characteristics of their geodatabase. After intensive experimentations, we found that the outcome of the ArcGIS online was not discernably better than that of the Desktop ArcGIS toolbox.

Some respondents reported inaccurate, partial, and erroneous addresses, but many of the problematic addresses appeared to be formatted correctly, so the research team was able to clean and geocode these addresses through a multiple iteration geocoding process. Four types of addresses were identified in the dataset, based on the type of information provided by the respondents:

1. Full addresses with street numbers;
2. Intersections of two closest streets;
3. One-street addresses; and
4. Only the name of cities and/or ZIP code[2].

Each type of address presents unique challenges that affect the geographic accuracy and precision of geocodes. Although misspells and the omission of some information in the street names are usually an easy fix, some of the reported full addresses did not exist (i.e., the street name is real, but the reported street number is not found on that street). Moreover, we found a nontrivial number of cases with two nearby streets which actually do not cross each other: not all people are able to correctly remember two intersecting streets nearby their residential

[2] The survey required each respondent to report a valid ZIP code. Thus, respondents that did not feel comfortable about providing additional information about their address, at a minimum provided information that allowed the research team to identify the city and ZIP code in which they live.

location, some respondents reported two streets that are actually parallel (and sometimes even far from each other). In addition, specific rules had to be defined to treat cases in which the survey participants reported only one street instead of their residential address. The research team had to develop a set of rules to assign the most likely Census tract to these respondents' residential, study, and work addresses. Lastly, cases with only information about the ZIP code had the lowest quality of information: ZIP code areas are often large enough to cover various types of neighborhoods (e.g. they can include both suburban and urban neighborhoods).

As an online search engine that is specialized to return reliable outcomes even with incomplete and partially incorrect key words, Google Maps API works on one of the most updated geodatabases and produces a rich set of information on the quality of geocodes, which users can use to examine geocoding outcomes. Because the geodatabase of Google Maps API is incorporated with the satellite images of Google Maps, Google Maps API produces a result from a direct search, instead of geographic referencing based on the first and last street numbers of street segments (which is how the Desktop ArcGIS toolbox and the online ArcGIS work). Moreover, for each query, Google Maps API returns addresses that it finds from its geodatabase and types of geocoding that it uses: thus, Google Maps API presents two ways of examining the quality of a geocode. First, users can compare input and output addresses and determine how similar the output address from Google is to the input address (also in case of incomplete and partially incorrect addresses). In addition, two categorical variables help users determine how reliable individual geocoding outcomes are.

Table 1 summarizes the number of cases in the dataset, by the type of address that was reported (and geocoded): 1,858 cases had highly reliable addresses (with full address or two-street intersections), 233 were moderately reliable (one-street addresses), and 64 were less reliable cases (with only city names and/or ZIP codes).

Table 1. Type of Addresses Geocoded in the Dataset

Quality of geocoding of residences	Number of cases
Full addresses or intersections of closest two streets	1,858 (86.2%)
One-street addresses	233 (10.8%)
City names and ZIP codes	64 (3.0%)
Total	2,155 (100%)

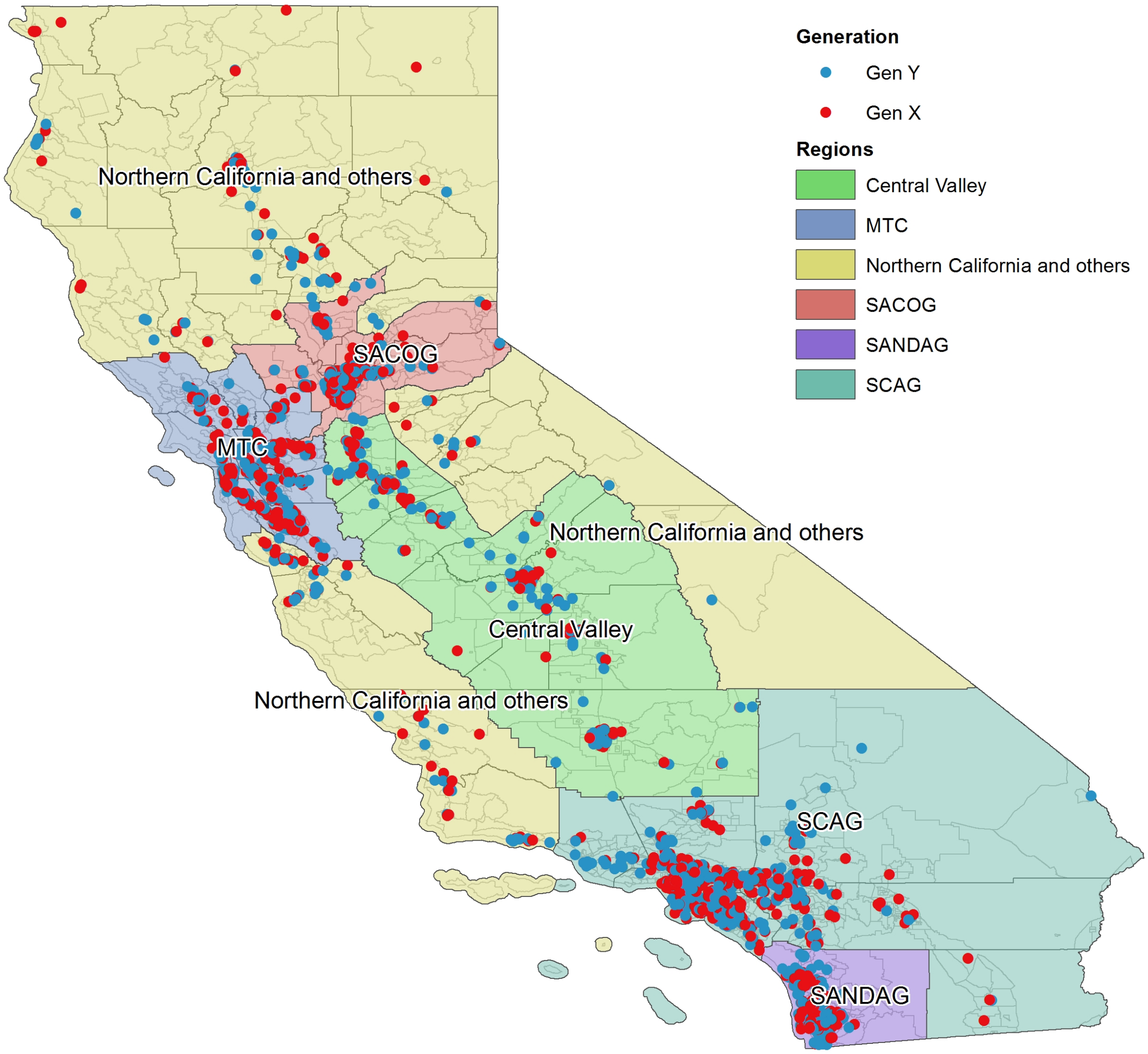

Figure 1. Distribution of millennials and Gen Xers in the dataset, based on their geocoded residential address

The outcomes of the geocoding of residential addresses helped the research team determine the type of neighborhood where the respondents live in California. This project uses the neighborhood type developed in another project from researchers at UC Davis, which analyzed and clustered the 8,036 census tracts in California based on the predominant neighborhood characteristics (Salon, 2015). The project classified each census tract as belonging to one of five categories: Central City, Urban, Suburb, Rural-In-Urban, and Rural. Because geocodes with one-street addresses and with city names and ZIP codes do not present the exact locations of residences, the research team visually inspected these cases to see whether or not their neighboring Census tracts also have similar neighborhood characteristics. If both the identified census tract and the neighboring census tracts show the same type of land-use patterns, even in the case of low quality of the geocoded location (i.e. one-street addresses or city names and

ZIP codes), the research team was able to assign the neighborhood type with a good margin of reliability. In contrast, if one's own neighborhood type differs from that of its neighboring Census tracts, we used the perceived neighborhood types that the individuals reported in the survey to determine which types of neighborhoods the respondents are likely to live in. Figure 2 summarizes the distribution of cases in the dataset by neighborhood type.

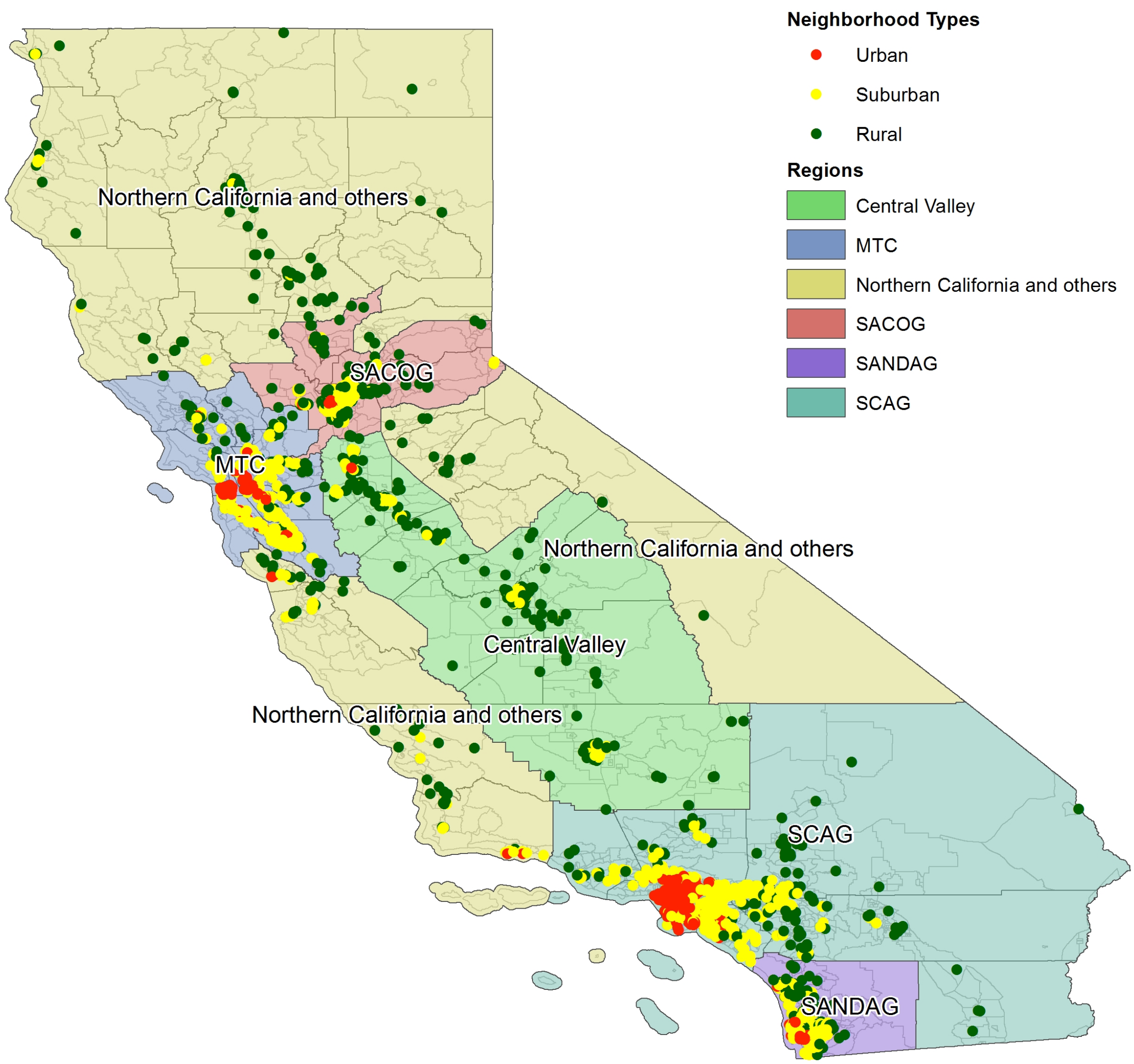

Figure 2. Distribution of cases in the dataset, by geocoded residential address and neighborhood type

Weighting and Raking

In order to correct for non-representativeness of the sample, and replicate the distribution of the population of Millennials and Generation X living in California, we used a combination of cell weighting and iterative proportional fitting (IPF) (Kalton & Flores-Cervantes 2003). We used cell weights to weigh our sample on three dimensions – *age group* (18-24, 25-34, 35-44, 45-50), *neighborhood type* (Rural, Suburban, Urban), and *region* (Central Valley, Northern California and Others, SACOG, SANDAG, SCAG, SF MTC). This weighting process compensates for the effects of the quota sampling process used in the data collection and the intentional oversampling of some regions. We intentionally underrepresented the residents of major metropolitan areas, mainly Los Angeles and to a lower extent San Francisco, in the data collection, and oversampled individuals who live in other areas (rural counties and less populated regions), in order to collect enough respondents for each region, and build robust analyses for all subsamples. At the time the study was launched, we envisioned a sample of at least 700 cases selected among the population of California millennials for this research. The size of the sample size was later increased through the recruitment of additional participants in the study, and also a control group composed of members of Generation X, which was not included in the original scope of the research, was added, further enriching the diversity of respondents in the sample. While any remaining sampling bias can limit the validity of the generalization of the results from this sample to the population of interest, the method used in this study remains very valid for comparisons among the two subsamples of millennials and members of Gen X, who were recruited with the same methodology. The sampling method that controlled for the distribution of each subsample on several sociodemographic traits and the application of weights allow us to build robust analyses of these data.

To develop our baseline population that was used to develop the target for the cell weights, we used the American Community Survey 2014 1-year estimate data paired with residential neighborhood classification data from Salon (2015). While, the residential neighborhood types for California census tracts were derived from Salon (2015), we aggregated the five neighborhood types determined in that study to three major neighborhood types, where Rural-in-Urban and Rural areas were classified as “Rural” and Center City and Urban areas were classified as “Urban”. Suburban areas were treated as “Suburban” consistent with the five neighborhood type classification. We used the ACS data to build a cross tabulation based on age group by region and neighborhood type. The final set of cell weights were generated by comparing the cross tabulation of survey respondents and the population of California residents ages 18 to 50.

In addition to cell-weighting on the three dimensions described above, we used multiple rounds of iterative proportional fitting (IPF) raking to mirror the distribution of the California population on several additional demographic targets. This allowed us to correct the distributions in the sample by assigning specific weights to our sample based on six dimensions – *race, ethnicity, presence of children in the household, household income, student/employment status*, and *sex*, which were used as targets in the IPF process. We used 1-year estimates of the

Public Use Microdata (PUMS) from 2015 to create the targets for the California population from 18-50 (U.S. Census Bureau 2014).

A total of three iterations of the IPF method was applied in this process. For the first round of application of IPF, we used the cell weights as the starting weights, and weighted on household income, student/employment status and sex. The annual household income was classified in three broad categories: Low (<$35,000), Medium ($35,000-$100,000) and High (>$100,000). Student/Employment status was classified through a four-level variable, where the participant may be unemployed, work only, be a student only, or be both a student and worker.

The second round of IPF used the weights generated by multiplying the cell weights and the first round of IPF and weighted these on Race and Ethnicity. Due to issues related to our sample size, we consolidated the race categories in the dataset as three main race groups – White, Asian/Pacific Islander, and Other. For Ethnicity, we used the two categories of Hispanic and Non-Hispanic.

The third round of IPF used the results of the previous iterations and weighted on Generation and Presence of Children. Generation was defined as Generation Y/Millennials (individuals who were 18 to 34 in 2015), and Generation X (individuals who were 35 to 50 in 2015). The presence of children in the household was measured with a binary variable (children, no children). Table 2 summarizes the descriptive statistics for both the unweighted and weighted dataset. The number of weighted cases in each group may not sum exactly to 2155 due to rounding effects.

Table 2. Demographic Statistics in the California Millennials Dataset

	Weighted		Unweighted	
	Number of cases	Percentage of total	Number of cases	Percentage of total
Total	2155	100%	2155	100%
Gender				
Male	1043	48.4%	876	40.6%
Female	1090	50.6%	1257	58.4%
Transgender	9	0.4%	8	0.4%
Decline to Answer	13	0.6%	14	0.6%
Presence of Children in the Household				
Household without Children	1018	47.3%	1089	50.5%
Household with Children	1137	52.7%	1066	49.5%
HH income				
Prefer not to answer	142	6.6%	158	7.3%
Less than $20,000	167	7.7%	207	9.6%
$20,001 to $40,000	357	16.6%	392	18.2%
$40,001 to $60,000	311	14.4%	374	17.4%
$60,001 to $80,000	294	13.6%	356	16.5%
$80,001 to $100,000	194	9.0%	236	11.0%
$100,001 to $120,000	225	10.4%	157	7.3%
$120,001 to $140,000	120	5.5%	81	3.8%
$140,001 to $160,000	133	6.2%	75	3.5%
More than $160,000	213	9.9%	119	5.5%
Age				
Younger Millennials (18 - 24)	473	21.9%	385	17.9%
Older Millennials (25 - 34)	714	33.1%	830	38.5%
Younger Generation X (35-44)	608	28.2%	613	28.4%
Older Generation X (45 - 50)	361	16.7%	327	15.2%
Ethnicity				
Hispanic	907	42.1%	501	23.2%
Non-Hispanic	1248	57.9%	1654	76.8%
Race				
Black/African American	88	4.1%	98	4.5%
American Indian/Native American	49	2.3%	40	1.9%
Asian/Pacific Islander	326	15.1%	332	15.4%
White/Caucasian	1269	58.9%	1399	64.9%
Other/multi-racial	422	19.6%	286	13.3%
Education				
Prefer not to answer	8	0.4%	8	0.4%
Some grade/high school	44	2.0%	42	1.9%
High school/GED	242	11.2%	278	12.9%
Some college/technical school	595	27.6%	642	29.8%
Associate's degree	232	10.8%	242	11.2%
Bachelor's degree	710	32.9%	686	31.8%
Graduate degree (e.g. MS, PhD, MBA, etc.)	227	10.5%	197	9.1%
Professional degree (e.g. JD, MD, DDS, etc.)	98	4.5%	60	2.8%
Average HH size	3.24		3.20	
Average # of Vehicles in the HH	1.88		1.80	

Integration of Additional Land Use Data from Other Sources

Knowing the location of work/school and home address of the respondents enables us to integrate our dataset with other existing data including Smart Location Dataset prepared by the U.S. Environmental Protection Agency (EPA), and other land use accessibility measures including the walk, bike and transit scores from other well-established sources (e.g. Walkscore.com). The Smart Location Database summarizes numerous demographic, employment information, and provides various statistical and deterministic built environment indicators estimated at the census block group (CBG) level (Ramsey & Bell 2014) [3]. These demographic and land use indicators were matched to individuals' residential and work/school location based on the geocoded location of the self-reported address.

The built environmental attributes that are measured in the Smart Location Dataset can be classified into five main categories:

- *Density* indices: The Smart Location Dataset provides different measure of density, including population, housing, activity and total number of employment and employment by type for each census block group.
- *Diversity* indices: Different measures of land use diversity were estimated for each census block group, including job to household balances, entropy indices for 5-tier and 8-tier employment categories, employment and household entropy based on trip production and attractions, trip equilibrium index, regional diversity, and household workers per job.
- *Urban design* indices: These indices estimated various urban design measures including street network density and intersection density by automobile, pedestrian and multimodal facilities. Example of these variables are network or intersection density in terms of auto-oriented links per square mile in each census block group.
- *Transit* indices: Using the Google transit data (particularly the location of transit stops and their regular schedule), the Smart Location Dataset provides different measures of transit availability, proximity, frequency and density. The transit variables are comprised of distance from the population-weighted centroid to the nearest transit stop, the proportion of block group within a quarter mile or half mile of a transit stop, the aggregated frequency of transit service per hour during the evening peak period, and the aggregate frequency of transit service per square mile. These transit measures are only estimated for the areas for which the corresponding transit agencies provided the required information.
- *Destination accessibility* indices: These indicators are developed to measure the accessibility from census block group to census block group. These variables measure the number of jobs or working-age population within a 45 minutes commute by car or

[3] The 2010 Census Tiger Line/polygons were used in defining block group boundaries, which were later merged with the information obtained from the other datasets including the 2010 Census data, the American Community Survey, the Longitudinal Employer-Household Dynamics, InfoUSA, NAVTEQ, PAD-US, TOD Database, and Google Transit Feed specification (GTFS) database.

transit from a certain block group. In addition, the EPA Smart Location Dataset includes relative measures of accessibility for each census block group based on the comparison with the accessibility of the census block groups that are located within the same metropolitan areas.

Furthermore, by using the latitudes and longitudes of all homes and workplaces, we can append additional variables that capture the characteristics of specific locations and that are available from reliable public and private databases. In particular, Walkscore.com has been known for its composite measure of walkability, the "walk score," which many scholars have found a useful variable to understand relationships between the built environment and non-motorized travel patterns. While not perfect[4], Walkscore.com provides three measures — *walk score*, *bike score*, and *transit score* — that capture the easiness of using various travel modes at specific locations. Since Walkscore.com provides an API service, the research team was able to extract the three score measures based on the latitudes and longitudes of the geocoded residential location of each respondent. These measures provide a good proxy of the supply-side characteristics of various neighborhoods across California.

With the geographic geocodes of homes, schools, and workplaces of all individuals in the dataset, in future stages of this project we plan to further enrich the California Millennial Dataset with a variety of transit and land-use variables from other reliable sources such as AllTransit.com and Google. The Alltransit.cnt.org website provides a wide array of matrices on the performance of local public transportation systems for individual census block groups. By employing the general transportation feed specification (GTFS) datasets that transit agencies maintain, and directly collecting information about transit services from the agencies without GTFS datasets, the website returns a rich set of variables under six categories, such as jobs, economy, health, equity, transit quality, and mobility.

In addition, two among the various Google API services, the Google Places API and Google Direction API, provide unique information that we plan to use in future stages of the project to analyze the location choice and the mode choice of Millennials and Gen Xers. The Google Places API provides the geographic coordinates of a diverse set of businesses. As users and business owners can ask Google to correct critical information such as opening and closing of businesses, Google Places API provides the highly accurate geographic locations of businesses by type. The Google Direction API calculates the distance and duration of a trip from an origin to a destination by four modes – driving, transit, biking, and walking – based on realistic congestion information that varies by time of day by using their archived traffic data.

[4] Walkscore.com measures its scores based on the accessibility to public places. However, the definition of public places has been questioned, as some places that are classified as "private", but do provide free access to the public and therefore could qualify for the definition of potential destinations for trips, are not considered in the computation of the scores.

Factor Analysis

In this section, we discuss the variable dimension reduction method that was applied on the attitudinal statements from sections A and J of the survey. The attitudinal variables were measured asking the respondents for their agreement with 66 statements using a 5-level Likert type scale (from strongly disagree to strongly agree). The 66 attitudinal statements were designed to measure the individual's attitudes related to 28 pre-determined unobservable constructs, including attitudes toward biking, car ownership, changes vs. routine, environmental concern, land use, masculinity, role of government, multitasking, etc. These attitudinal constructs can explain variability in decisions about car ownership, travel mode choice, residential location and many other decisions that made by different segment of population.

As discussed earlier, out of 2155 respondents 191 individuals have failed in answering correctly to one of the trap questions included in the survey. Three trap questions were embedded in the sections A and G of the report, to control for the quality of the responses. Information related to the individuals who failed two or more trap questions was automatically removed from the dataset. The remaining 191 cases that failed only one trap question are expected to contain lower quality information, which could skew the result of the factor analysis and significantly change the factor extraction and loading process. Hence, we only performed the final factor analysis on the individuals with higher quality of the responses, i.e. the respondents who did not fail any trap question (N=1964 cases).[5]

The first and most challenging step in factor analysis is to determine the number of factors to be extracted. The default in most statistical software packages is to retain all factors with eigenvalues greater than 1.0 or greater than a value close to one, e.g. 0.7 (as discussed by Jolliffe, 1972). On the other hand, Velicer and Jackson (1990) showed that using this criterion may lead to too many extracted factors. Using a Monte Carlo simulation, the authors found that 36% of the samples retained too many factors using this criterion. Hence, alternative approaches (based on multiple criteria) have been recommended to identify the number of factors, including scree test plot, Velicer's MAP criteria, parallel analysis, and most importantly the interpretability of the extracted factors.

Based on multiple criteria including the evaluation of the eigenvalues, scree plot, strength of the relationship, and interpretability, a range for the number of factor was first identified. Then factor solutions with those numbers were tested to see which solution produces the best outcome conceptually and numerically. As expected, some variables were found to have small loadings on any factors (smaller than 0.29). In the other words, some statements did not load on any factors in any meaningful way. These standalone statements either belongs to single statement construct (e.g. "I like riding a bike" is a good attitudinal variable that can be used in isolation to predict bicycling behavior) or perceived differently by respondents (e.g. statement

[5] We compared the results from a factor analysis that was performed on the full dataset, which included also these lower quality cases. The comparison confirmed the higher amount of noise in the solution that was estimated using the full dataset.

used for capturing the effects of peer pressure are often difficult to be used in behavioral research due to the reluctant attitude of most respondents to report peer pressure, and social desirability bias). Additionally, some statements with weak factor loadings were included in factors measuring a completely different attitudinal construct. For example, attitudes toward masculinity (or *machismo*), which were measured by statements including "It is more important for men than for women to have a high-paying career" and "At work, it's perfectly fine for women to have authority over men", loaded well in the factor that measured the *pro-environmental policy* attitudes of individuals. This, while is a sign of another latent attribute of individuals (e.g. which measures some conservativism, or traditional thinking), makes the interpretability of the factor more complicated, in terms of their relationship with environmental choices, and travel behavior. For this reason, those two statements were removed from the factor analysis. Table 3 shows the 14-standalone statements that are excluded from the factor analysis. One can use these standalone statements as an ordinal or as a standardized variable for descriptive statistics and as explanatory variables for modeling purposes, even if the statements are not included in the factor analysis.

Table 3. Standalone Statements

Attitudinal Statements
I would pay money to reduce my travel time.
It is more important for men than for women to have A high-paying career.
At work, it is perfectly fine for women to have authority over men.
I avoid doing things that I know my friends would not approve.
Background music/radio/TV is too distracting for me.
I like sticking to a routine.
I try to make good use of the time I spend commuting.
I like riding a bike.
I feel positively about the level of investment occurring in my local roads and local transit.
The air quality in the region where I live concerns me.
Having children means you have to have a car.
Individuals should generally put the needs of the group ahead of their own.
It is pretty hard for my friends to get me to change my mind.
I am uncomfortable being around people I do not know.

After careful analysis of the results and excluding the standalone statements, we performed the factor analysis on the 52 remaining statements. Based on multiple criteria, a total number of 17 factors were identified. The following subsections summarize the criteria that were used to determine the optimal number of factors.

Eigenvalue greater than one (or value close to one)

Table 4 shows the initial eigenvalues for different number of factors. As indicated in this table, 16 factors have eigenvalues greater than 1.00 and 10 factors have eigenvalues between 0.99 and 0.7. Hence, the optimal number of factors could be in the range between 16 and 26.

Table 4. Eigenvalues

Factor	Initial Eigenvalues	Factor	Initial Eigenvalues	Factor	Initial Eigenvalues
1	4.88	21	0.81	41	0.48
2	3.66	22	0.80	42	0.46
3	2.84	23	0.77	43	0.44
4	2.69	24	0.75	44	0.44
5	2.21	25	0.74	45	0.43
6	1.81	26	0.72	46	0.42
7	1.64	27	0.68	47	0.40
8	1.57	28	0.68	48	0.40
9	1.51	29	0.65	49	0.37
10	1.28	30	0.64	50	0.35
11	1.26	31	0.63	51	0.34
12	1.20	32	0.62	52	0.21
13	1.12	33	0.59		
14	1.10	34	0.59		
15	1.03	35	0.56		
16	1.01	36	0.55		
17	0.91	37	0.55		
18	0.90	38	0.54		
19	0.84	39	0.53		
20	0.84	40	0.50		

Scree test (i.e. elbow rule)

The second criteria for choosing the number of factors was the scree test. According to this criterion the percent of variance explained by the individual factors would "level off" as the solution reaches the most appropriate number of factors. Beyond this number of factors, additional factors would account for random errors. This rule should be applied to a final un-rotated solution. Using all 52 statements used in the factor analysis, we plotted the changes in variance explained by different numbers of factor. The result indicates that the desirable number of factors can be between 10 and 17 (where the percent of variance explained by individual factors started to level off).

Strength of the relationship

In this criterion we checked whether the rotated factor loadings are greater than |0.3|. To identify non-trivial factors that could be obtained, researchers use different cut-offs. Some researchers use more relaxed criteria such as a cut-off of |0.2|, which seems very low, and some others use very stringent criteria such as a cut-off of |0.7|. In our study, we used a cut-off value of |0.3|.

Interpretability

"Variables that load near 1 are clearly important in the interpretation of the factor, and variables that load near 0 are clearly unimportant. Simple structure thus simplifies the task of interpreting the factors" (Bryant and Yarnold, 1995, page 132-133).

Thus, for simplicity we controlled that all loaded statements conceptually convey a similar content (construct). As discussed earlier, for example, we had to exclude the masculinity/machismo statements, which loaded on the pro-environmental policy factor (with negative direction): these two groups of statements seem to capture rather different constructs.

Table 5. Moderately Correlated Factors

Factor or variable	Factor or Variable	Correlation
Pro-environmental policies	Must own car	-0.356
Pro-environmental policies	Responsive to environmental effect and price of travel	0.301

Using the above criteria ensures the robustness and validity (convergent validity and discriminant validity) of the factor solution. Furthermore, due to existence of correlation among factors (see Table 5 for the most highly correlated factors, with correlations higher than |0.3|), we chose an oblique rotation: oblique rotation may show some levels of correlation among factors, which is not ideal in statistical analysis, but it can capture individual factors that are better supported by the data, because it allows to have factors that are not orthogonal to one another.

The factor analysis extraction method that was used for the final solution was the maximum likelihood method. This method produces parameter estimates that are most likely to have produced the observed correlation matrix if the sample is from a multivariate normal distribution (as reported in the IBM's SPSS Manual). Maximum likelihood allows the computation of a wide range of goodness of fit measures and significance tests. The goodness of fit test of the final factor solution was statistically significant, with a value of chi-square of 1336.94, and a number of degrees of freedom equal to 578. The results of final factor solution are presented in Table 6.

Table 6. Final Results of the Factor Analysis

Factors and Loaded statements	Factor Loading
Pro-store shopping	
I prefer to shop in a store rather than online.	0.998
I enjoy shopping online.	-0.413
Pro-environmental policies	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.937
We should raise the price of gasoline to provide funding for better public transportation.	0.841
The government should put restrictions on car travel in order to reduce congestion.	0.331
Variety Seeking	
I like trying things that are new and different.	0.592
I have a strong interest in traveling to other countries.	0.405
Pro-exercise	
The importance of exercise is overrated.	-0.822
Getting regular exercise is very important to me.	0.587
Pleasant commute	
My commute is stressful.	-0.802
My commute is generally pleasant.	0.689
Traffic congestion is a major problem for me personally.	-0.544
The time I spend commuting is generally wasted time.	-0.501
Getting stuck in traffic does not bother me that much.	0.305
Pro-suburban	
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to.	0.764
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.	0.428
I like the idea of having different types of businesses (such as stores, offices, restaurants, banks, and library) mixed in with the homes in my neighborhood.	-0.357
Responsive to environmental effect and price of travel	
The environmental impacts of the various means of transportation affect the choices I make.	0.739
I am committed to using a less polluting means of transportation as much as possible.	0.598
The price of fuel affects the choices I make about my daily travel.	0.532
To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle.	0.384
Established in Life	
I'm already well-established in my field of work.	0.704
I'm still trying to figure out my career (e.g. what I want to do, where I'll end up).	-0.636
I am generally satisfied with my life.	0.387
Long term suburbanite	
I picture myself living long-term in a suburban setting.	0.819
A house in the suburbs is the best place for kids to grow up.	0.568
I picture myself living long-term in an urban setting.	-0.310
Must own car	
I definitely want to own a car.	0.697
I am fine with not owning a car, as long as I can use or rent one any time I need it.	-0.500
Car as a tool	

The functionality of a car is more important to me than its brand.	0.579
To me, a car is just a way to get from place to place.	0.480
Climate change concerned	
Greenhouse gases from human activities are creating major problems.	0.796
Any climate change that may be occurring is part of a natural cycle.	-0.656
It is pointless for me to try too hard to be more environmentally friendly because I am just one person.	-0.307
Technology embracing	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.609
Getting around is easier than ever with my smartphone.	0.492
Learning how to use new technologies is often frustrating.	-0.359
Technology creates at least as many problems as it does solutions.	-0.310
Monochronic (Pro-monotasking)	
It's best to finish one project before starting another.	0.518
I like to juggle two or more activities at the same time.	-0.346
Time/mode constrained	
My schedule makes it hard or impossible for me to use public transportation.	0.580
I am too busy to do many things I'd like to do.	0.443
Most of the time, I have no reasonable alternative to driving.	0.388
Pro-social	
Social media (e.g. Facebook) makes my life more interesting.	0.505
People are generally trustworthy.	0.442
I enjoy the social aspects of shopping in stores.	0.323
Materialism	
I would/do enjoy having a lot of luxury things.	0.441
I prefer to minimize the material goods I possess.	-0.412
For me, a lot of the fun of having something nice is showing It off.	0.387
I like to be among the first people to have the latest technology.	0.380
To me, owning a car is a symbol of success.	0.316

The Bartlett method was used for generating the final standardized factor scores. The resulting scores from this method are expected to be unbiased and, therefore, more accurate reflections of the cases' location on the latent continuum in the population.

Adoption of Technology, Individual Attitudes and Mobility Choices of Millennials vs. Gen Xers

The analysis of the California Millennials Dataset allows us to investigate several trends associated with the personal travel-related attitudes of millennials and their measures of travel behavior, and compare them with the attitudinal and behavioral patterns observed among members of the older Generation X. In this part of the report we summarize the observed trends in (1) the use of modern technologies, social media and smartphone applications for travel scheduling purposes, (2) the distribution of attitudinal patterns, as measured by the factor scores that were computed for all respondents included in the dataset, and (3) measures of travel behavior and adoption of shared mobility services, average accessibility in the place of residence and adoption of multimodal travel among various segments of the population. In particular, we focus on differences observed among various groups of millennials vs. older adults, based on the location where individuals live.

Figure 3 shows the use of social media such as Facebook to coordinate travel for non-work activities by age group (millennials vs. Generation X) and neighborhood type (urban, suburban and rural) where the individual lives. Not surprisingly, millennials are more inclined to frequently use social media to coordinate for their non-work related travel, with urban millennials being in particular the heaviest adopters of these services to coordinate their activities.

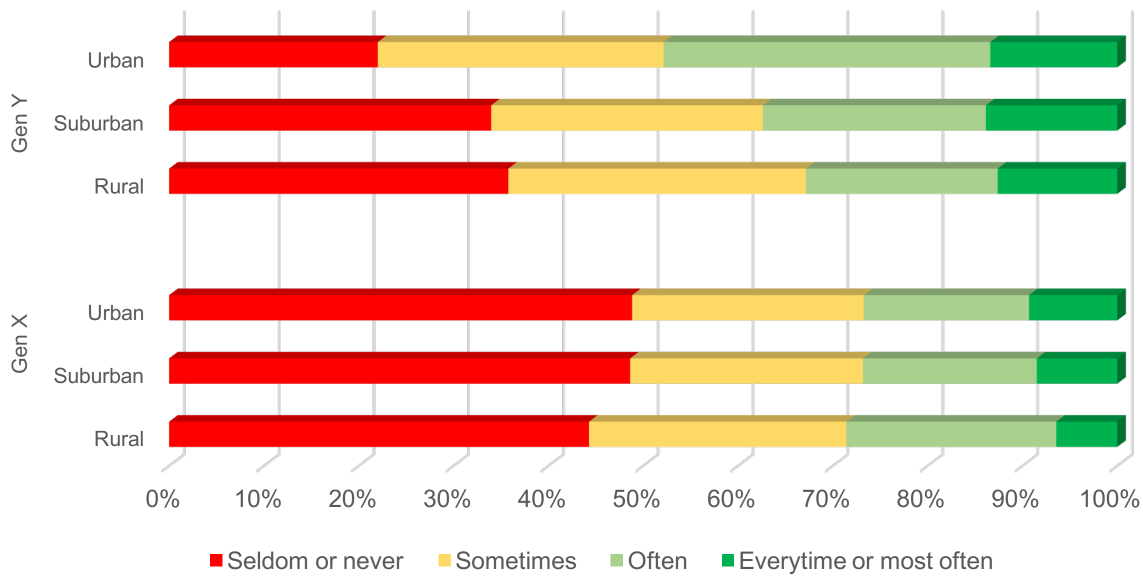

Figure 3. The use of social media to coordinate travel by age group and neighborhood type

Millennials also reported that they use smartphone in connection with their daily travel more often compared to their older counterparts. The following set of figures summarizes the use of smartphone to check traffic conditions (Figure 4), check when a bus or train arrives (Figure 5), decide what mode or combination of modes to use (Figure 6), learn how to get to/explore new places (Figure 7), and navigate in real time (Figure 8). In particular, and consistent with expectations, urban populations are found to use their smartphone more often for all these activities both among Millennials and Gen Xers.

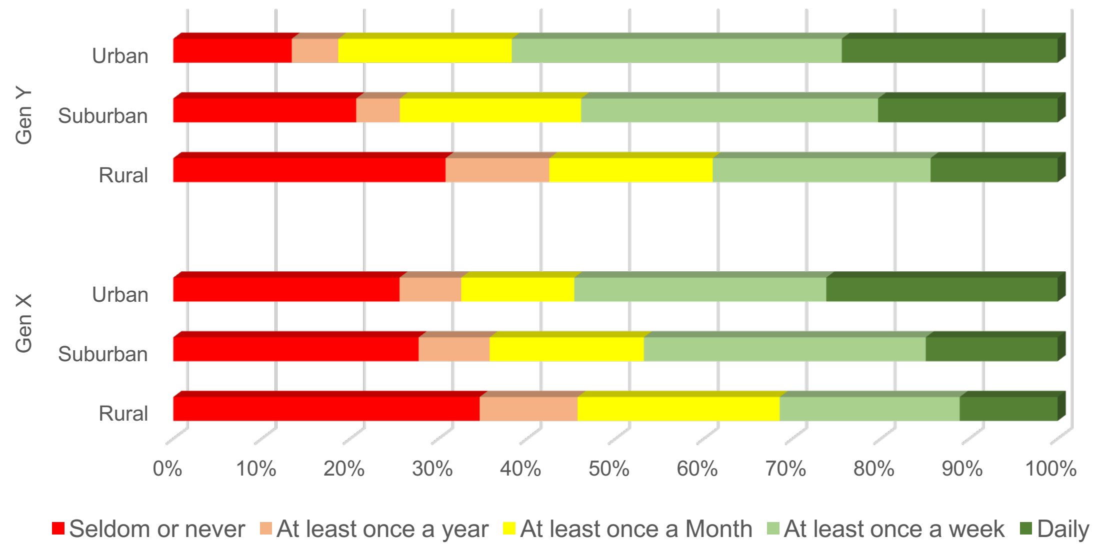

Figure 4. Use of smartphone to check traffic and to plan the travel route or departure time by age group and neighborhood type

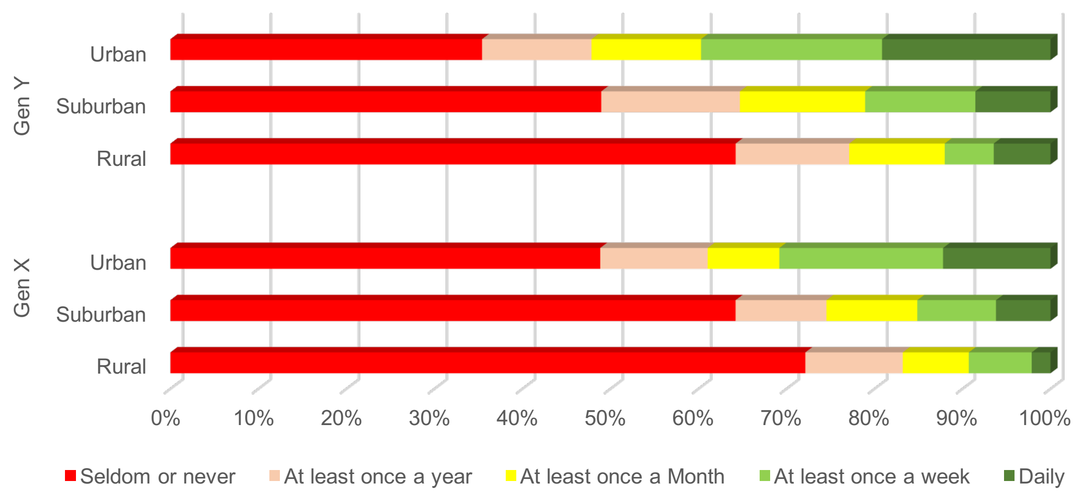

Figure 5. Use of smartphone to check when a bus or train will be arriving by age group and neighborhood type

The differences across neighborhood types are particularly large for the use of smartphone technology to check what modes of transportation, or combinations of modes, to use, which is likely to be an effect of the availability of multiple travel options in denser urban areas. In later sections of the report, we will return to discussing the measures of travel accessibility, by mode, for the members of the various generations. We plan to further investigate, in future steps of the research, how the use of these technologies, and the various levels of accessibility in the areas where individuals live, affect their travel patterns, an issue of significant importance to planning processes.

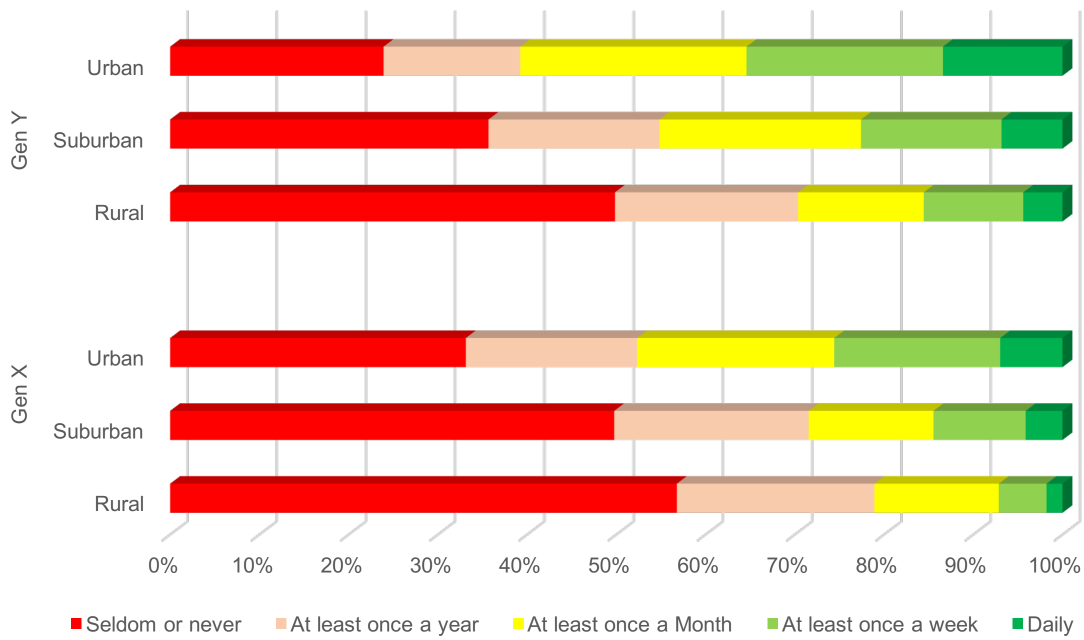

Figure 6. Use of smartphone to decide means of transportation to use by age group and neighborhood type

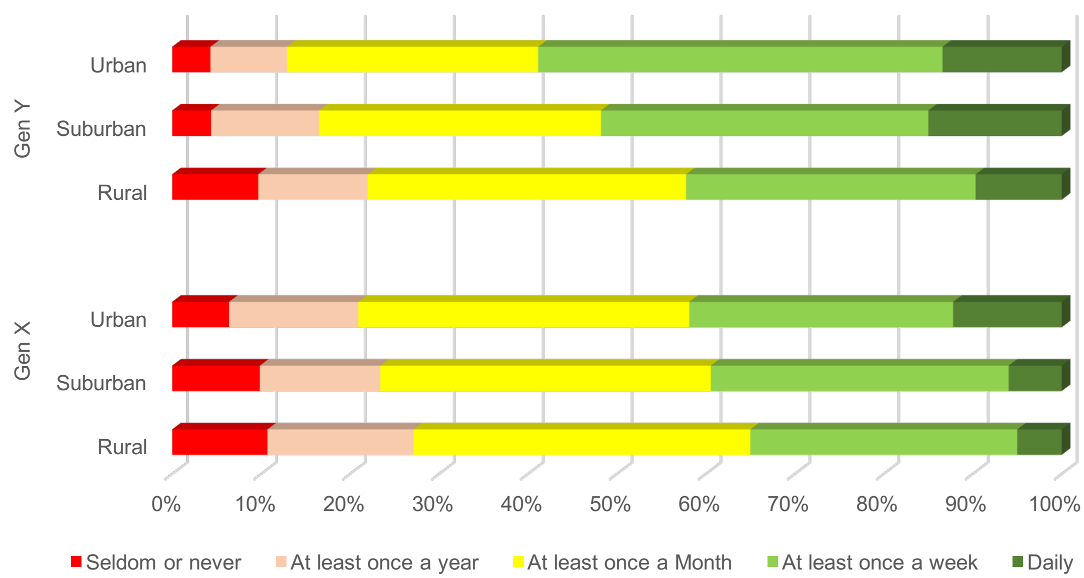

Figure 7. Use of smartphone to learn how to get to a new place by age group and neighborhood type

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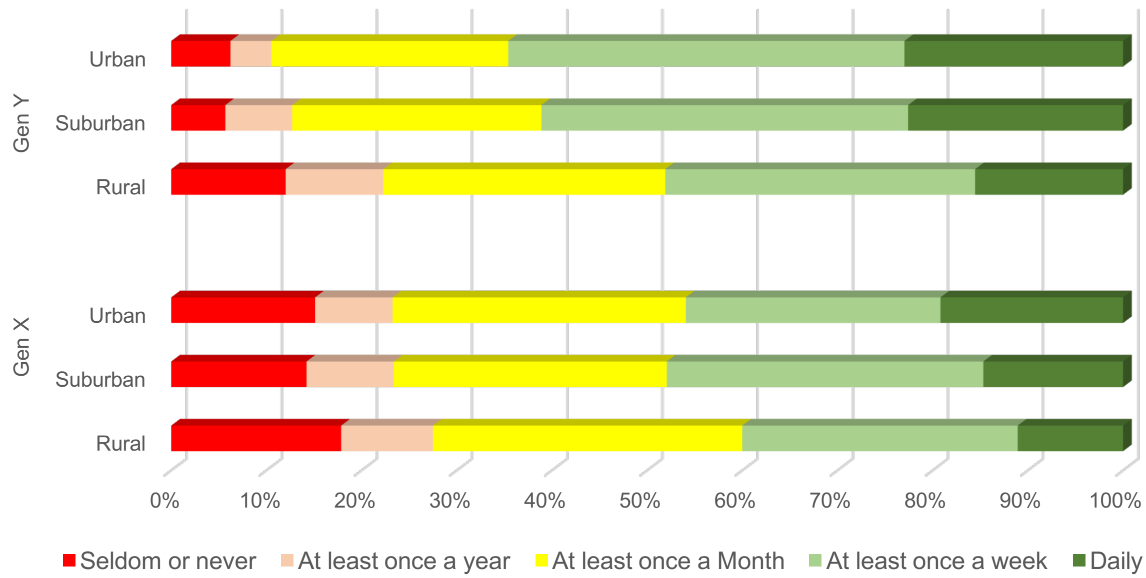

Figure 8. Use of smartphone to navigate in real time by age group and neighborhood type

Investigating Millennials' Attitudes towards Transportation and Technology

This section describes the differing attitudinal profiles observed among millennials and members of the Generation X by the neighborhood type they live in using the computed factor scores. Personal attitudes and preferences are likely to be important factors affecting individual choices related to housing, travel and activity scheduling. Still, to date, information about individual attitudes, preferences, and lifestyles is rarely collected in transportation surveys.

In this section, we explore how average attitudes differ among various segments of the population of millennials and Gen Xers who live in different neighborhood types, with respect to several constructs that were explored in the attitudinal section of the survey, and through the factor analysis presented in the previous chapter. The next set of figures presents the average factor scores (and 95% confidence intervals) for various groups of individuals, classified by age group and neighborhood type (urban/non-urban) in which the respondents live.

It is important to remind the readers that, as all figures in this section report information for the standardized factor scores (e.g. with zero mean, and variance equal to 1), any (eventual) differences across groups should be evaluated accordingly. For example, if a group has a moderately *positive* average factor score for the *pro-environmental policy* factor scores, that means that the individuals that belong to that group, on average, tend to have stronger pro-environmental policy attitudes, compared to the average for the entire sample (whose mean for this variable is zero).

Accordingly, the figures presented in this section should not be interpreted in terms of what individuals have a certain attitudinal characteristics (e.g. what groups are "pro-environmental policy") but, rather, in *relative terms* as a comparison across groups (e.g. the figures help answer the question "are the individuals that belong to the younger generations more likely to have higher "pro-environmental policy" attitudes than those that belong to the older generation? And what about urban vs. suburban residents?"). Similarly, in those cases in which all individuals in the sample eventually share a similar attitude towards a topic (e.g. positive "pro-environmental policy" attitudes), the comparison across groups of the average values for the standardized factor scores helps distinguish what groups of individuals tend to have even stronger attitudes (agree even more than others) with such attitudinal construct.

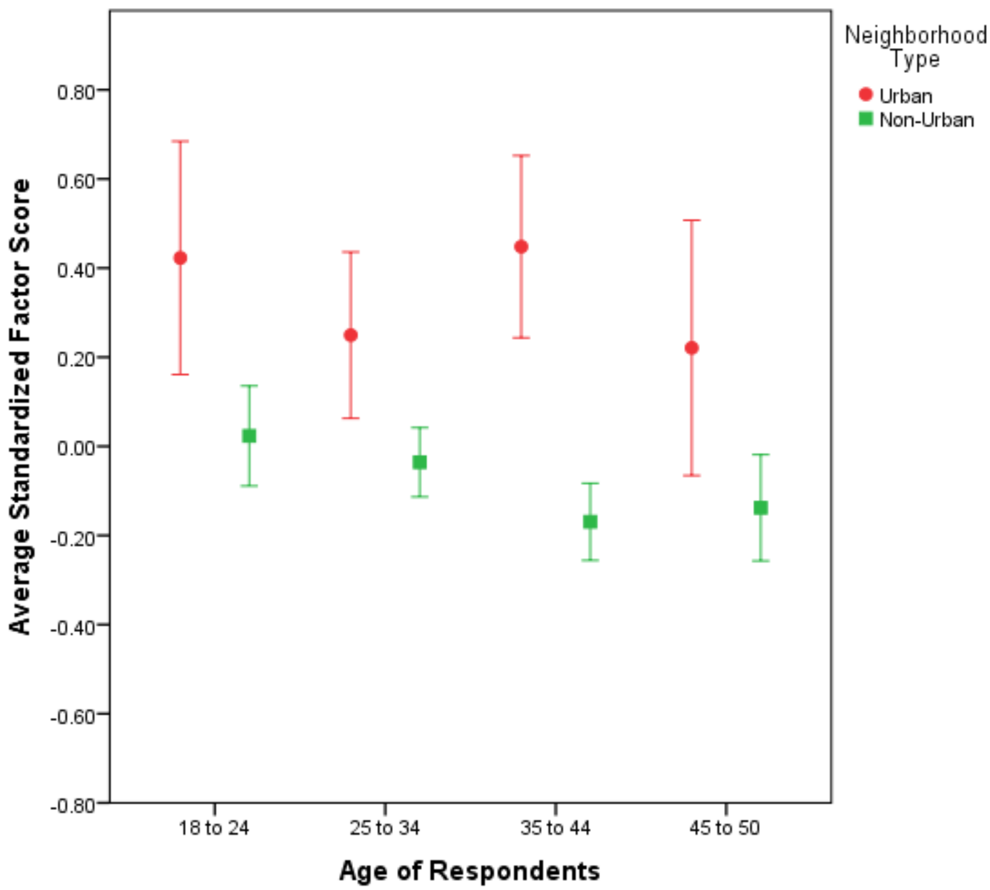

Figure 9. Average "pro-environmental policy" factor score by age group and neighborhood type (95% confidence intervals are reported in the figure for each group)

Figure 9 presents the differences in the attitudes toward pro-environmental government policy, as measured by the average factor score that was extracted in the factor analysis for individuals from both generations that live in urban vs. non-urban areas: individuals with a higher average factor score tend to have higher degree of agreement with the following statements: "We should raise the price of gasoline to reduce the negative impacts on the environment.", "We should raise the price of gasoline to provide funding for better public transportation." and "The government should put restrictions on car travel in order to reduce congestion."

Urban respondents of all ages appear to be higher supportive of pro-environmental policies, while non-urban residents' agreement with these statements appears to decline as the age of respondents increases. Urban residents, across all age groups, also present more heterogeneity for this attitudinal dimension, as shown by the larger confidence intervals around the mean.

Next, Figure 10 shows the average values for the *variety seeking* attitudinal factor score, by age group and neighborhood type. This factor captures individual levels of agreement with statements consisting of "I like trying things that are new and different" and "I have a strong interest in traveling to other countries". Urban respondents have higher scores across age groups, particularly in the age ranges of 25 to 34 and 35 to 44.

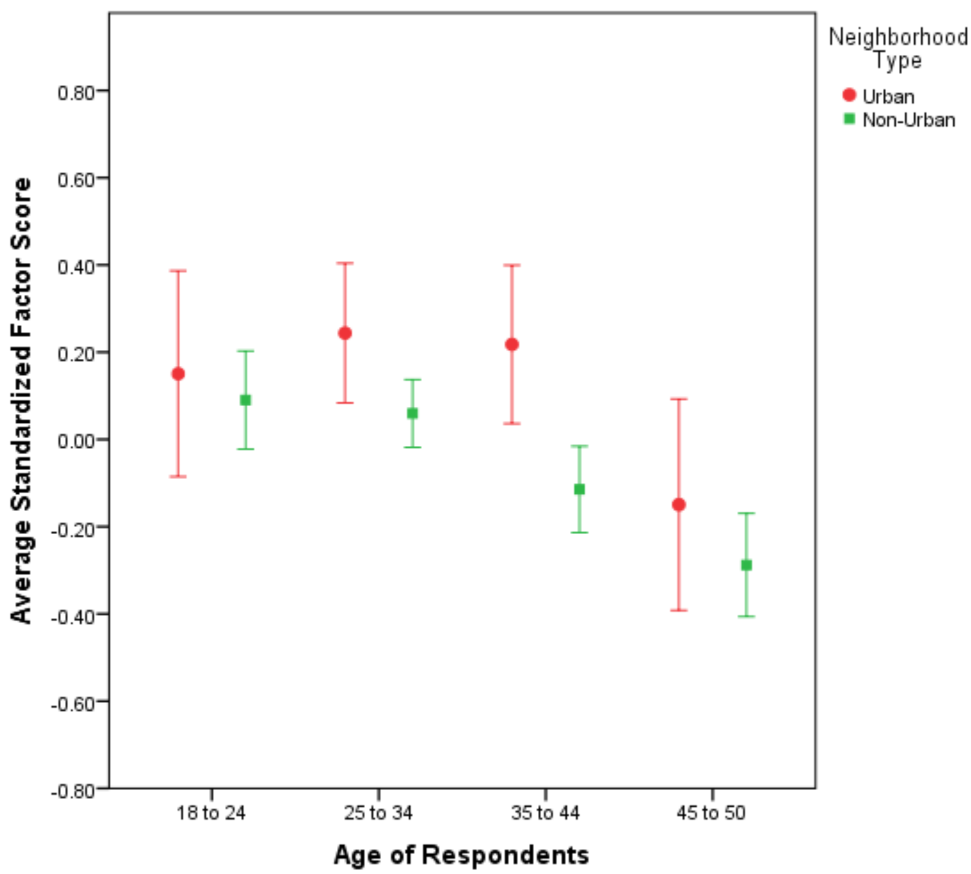

Figure 10. Average "variety seeking" factor scores by age group and neighborhood type (95% confidence intervals are reported in the figure for each group)

Again, much larger variance is observed among urban dwellers, probably as the combined effect of the heterogeneity associated with these groups of individuals, as well as the smaller sample sizes that are available for the urban subsamples.[6] Individuals in the highest age group (45-50) are those that have the lowest values for this factor score.

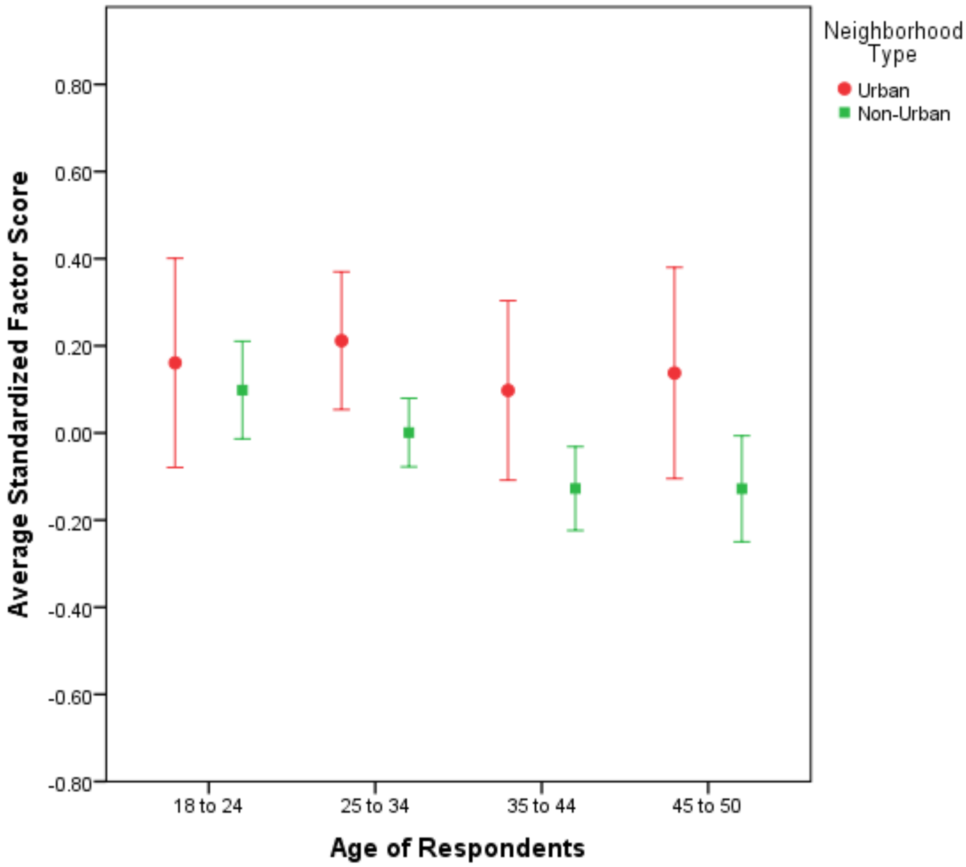

Figure 11. Average "responsive to environmental effects and price of travel" factor score by age group and neighborhood type (95% confidence intervals are reported in the figure for each group)

Figure 11 reports the responsiveness of travelers to price and environmental effect of transportation. Those that have a higher value for this factor score tend to agree with the following statements: "The environmental impacts of the various means of transportation affect the choices I make", "I am committed to using a less polluting means of transportation as

[6] Urban residents include various groups of individuals with different lifestyles, including groups of individuals who are in a transient stage of their life, younger individuals who are still developing their training and education, individuals that live with other roommates and housemates, temporary residents, professionals and other highly-educated workers, young couples with no children, members of minorities, etc. The proportion of temporary residents (and tenants who rent their housing units) is usually higher in urban areas, and the average turnover of residents in a housing unit is faster. In addition, a wide variety of urban neighborhoods exist, each with different characteristics and various levels of accessibility by various transportation modes.

much as possible", "The price of fuel affects the choices I make about my daily travel" and "To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle". This factor captures respondents' willingness to change their travel mode based on both the environmental impacts of transportation and gas price.

As indicated in Figure 11, urban respondents of all age groups have higher average factor scores than non-urban respondents. Interestingly, non-urban respondents' tendency to agree with these statements appears to decline by age group, with the individuals between 35 and 50 year old (Gen Xers) agreeing the least with these statements. However, among urban respondents, the average factor score appears relatively constant by age group. This may suggest that urban respondents of all ages view the environment positively and consider the environmental impacts of transportation-related decision as well as price of fuel when a making transportation choices. This may be also affected by the availability of more options (i.e. transit services, bike lanes and shorter distances that can be covered with various modes). Further, this attitudinal factor score might signal the behavior of individuals that may eventually self-select to live in an urban neighborhood type due to these underlying preferences (e.g. they moved to an area that better matches their preferences).

Figure 12 shows the differences in the average *climate change concern* factor score by age group and neighborhood type. Those that have higher values for this factor score tended to agree with the statement "Greenhouse gases from human activities are creating major problems", and tended to disagree with the following statements: "Any climate change that may be occurring is part of a natural cycle", and "It is pointless for me to try too hard to be more environmentally friendly because I am just one person."

The pattern of responses is similar to the factor measuring the agreement with the government intervention, where urban respondents have almost uniformly higher scores for this factor, while for non-urban respondents express lower concern for climate change, on average. Differences between urban and non-urban respondents tend to increase with age.

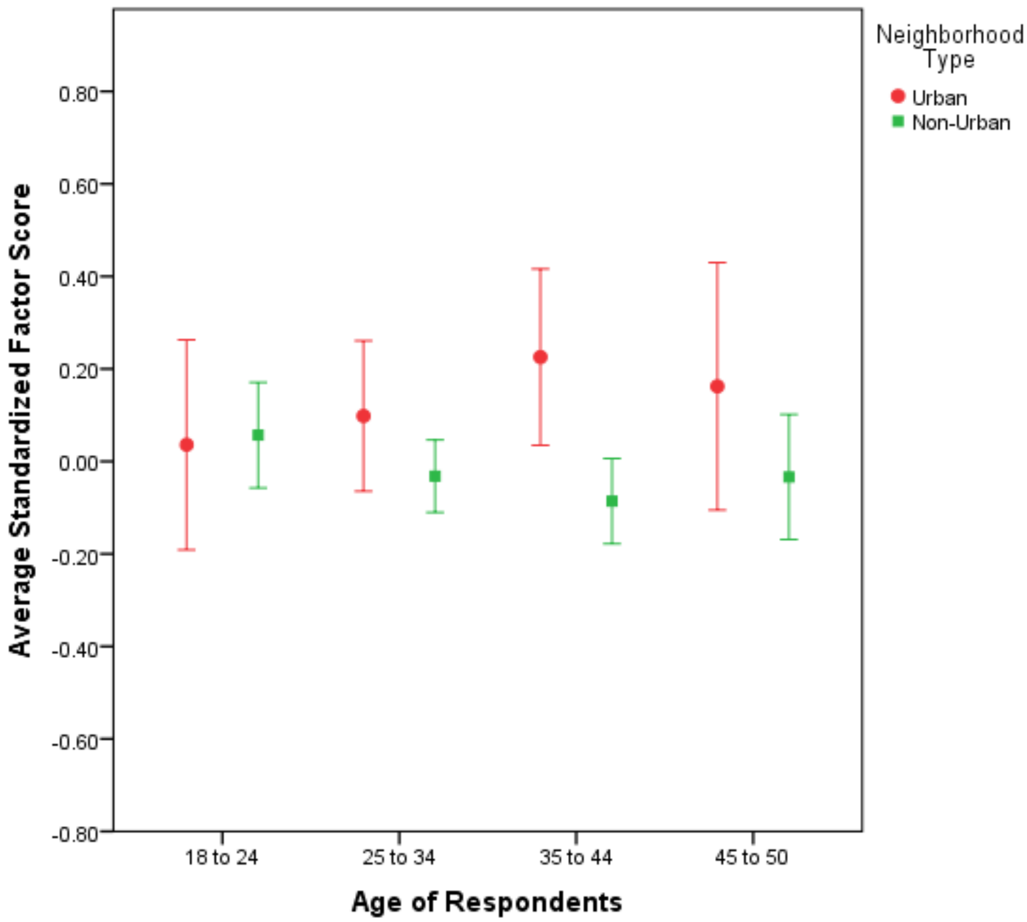

Figure 12. Average "climate change concerned" factor score by age group and the neighborhood type (95% confidence intervals are reported in the figure for each group)

Figure 13 reports the average values for the *established in life* factor score by age group and areas where the respondents live. This factor captures respondents' opinion about their life stage through their level of agreement with the statements "I'm already well-established in my field of work", "I am generally satisfied with my life", and "I'm still trying to figure out my career (e.g. what I want to do, where I'll end up)." It is not surprising to see that as individuals become more established in their life, their level of satisfaction increases (although this seems to counteract the stereotype of the optimistic millennial generation, who think positive even if they are in a transient stage of their life, as often reported by the media).

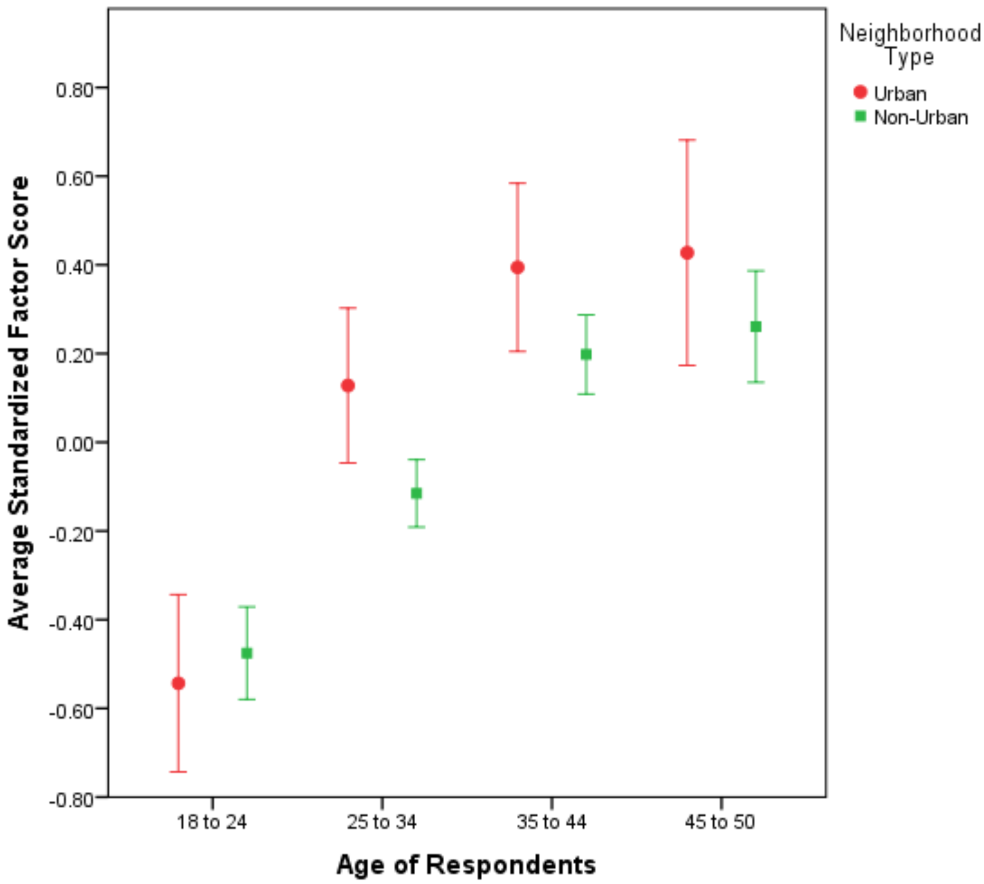

Figure 13. Average "established in life" factor score by age group and neighborhood type (95% confidence intervals are reported in the figure for each group)

Both life satisfaction and stability increases by age. Both younger and older millennials tend to have lower average scores than members of Generation X. This is unsurprising given that the millennials are often underemployed and in many cases still not independent (living with their parents), but large differences are observed between young and old millennials, with the urban millennials having the lowest average scores for this factor. Also for this factor, much larger variance is observed among urban dwellers, even if they, on average, have higher scores than their non-urban counterparts.

Figure 14 reports the average factor score and confidence interval for the *long-term suburbanite* lifestyle factor score. Those that have higher scores for this factor tend to agree with the following statement "I picture myself living long-term in an urban setting" and they tend to disagree with "I picture myself living long-term in a suburban setting" and "A house in the suburbs is the best place for kids to grow up."

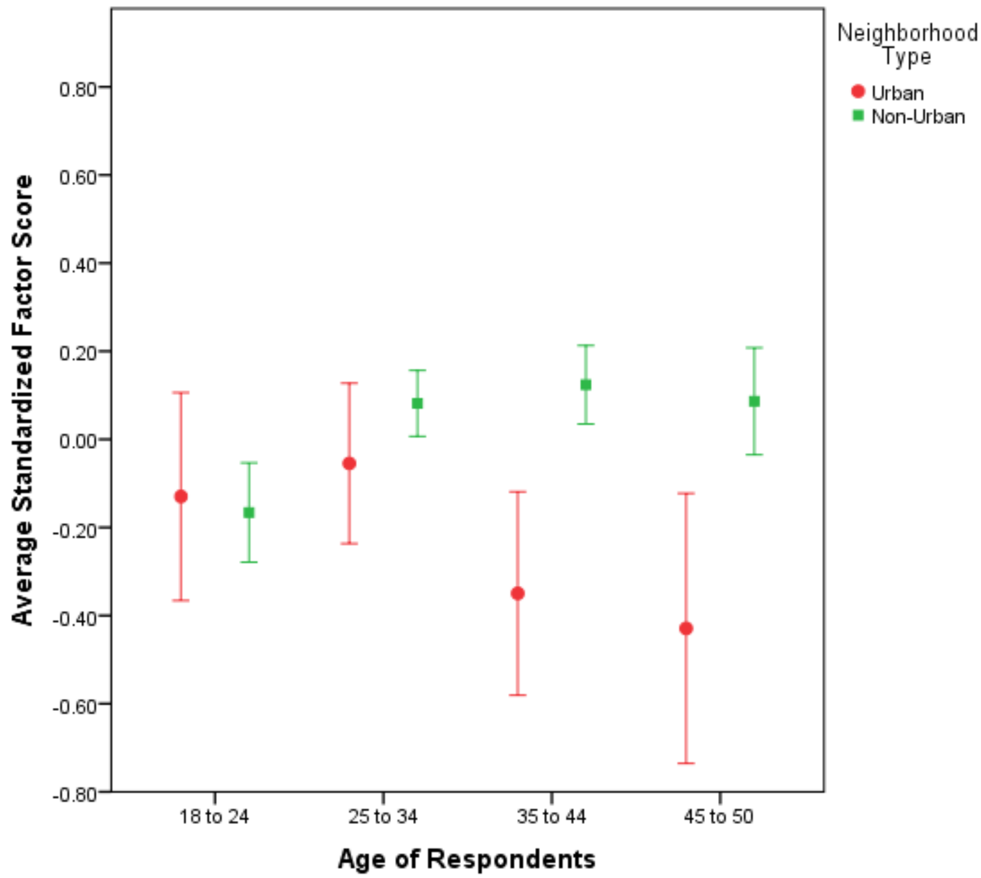

Figure 14. Average "long-term suburbanite" factor score by age and neighborhood type (95% confidence intervals are reported in the figure for each group)

In general, inclination toward suburbanite lifestyle is lower for individual living in urban neighborhood compared to their cohort living in suburban or rural areas. Not surprisingly, Gen Xers who live in suburban areas have the highest average scores for this factor. Very interestingly, and somewhat unexpectedly, though, the trend among millennials show that many millennials still see themselves living "long term" in a suburban area. This finding has extremely important planning implications: if confirmed by future decisions about residential location, the trend would confirm that the higher preference for central urban areas among millennials might be only a transition associated with their stage in life. Similarly, the hope of many policy-makers that millennials might continue to embrace urban lifestyles and continue to support the regeneration of the central areas of cities also as they age might not be fully supported, with important implications on the future demand for housing and travel.

Figure 15 presents the average factor score and confidence interval for the "must own a car" factor. Those that have high scores for this factor tended to agree with the following statement: "I definitely want to own a car" and disagree with the statement: "I am fine with not owning a car, as long as I can use or rent one any time I need it".

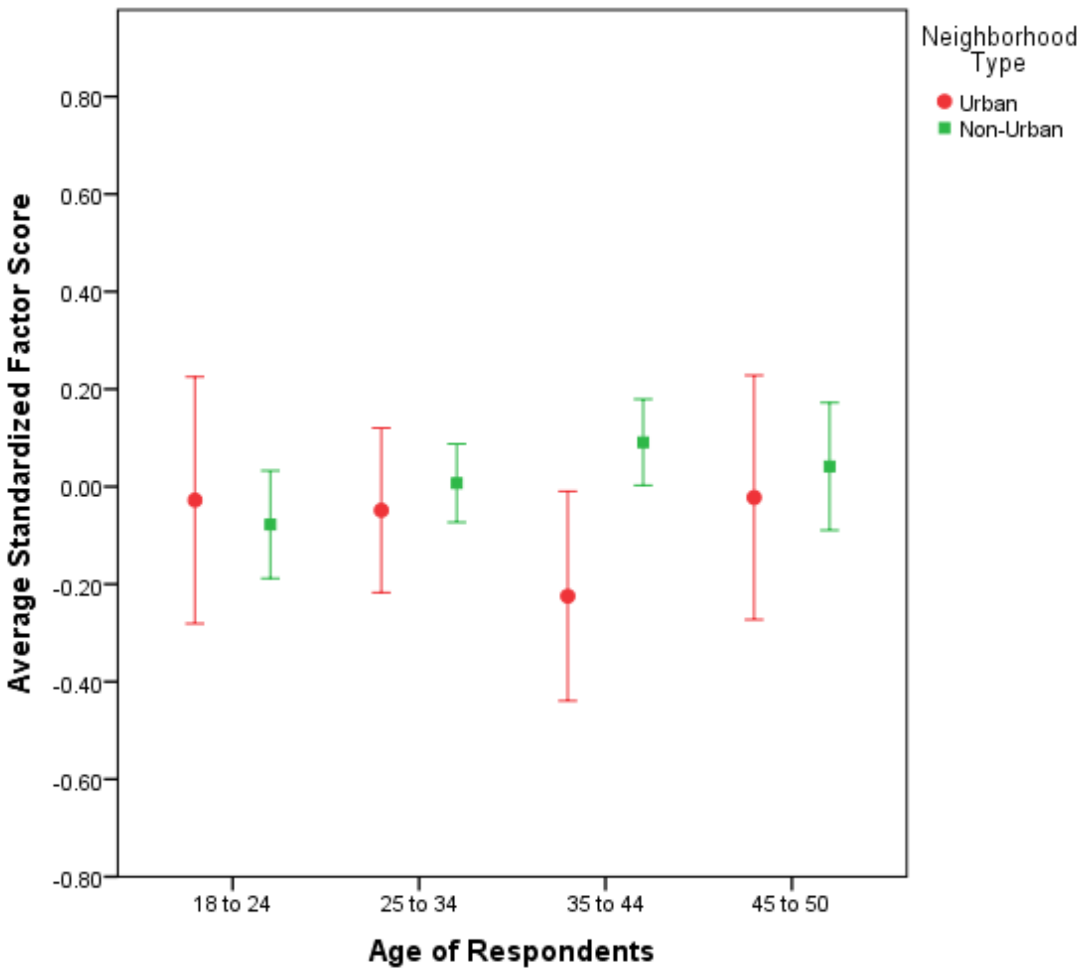

Figure 15. Average "must own car" factor score by age and neighborhood type (95% confidence intervals are reported in the figure for each group)

Except younger millennials, the urban respondents of all age groups tend to disagree with this factor, indicating that they are less inclined to own a car. For non-urban respondents, car ownership attitudes appear to be stronger with age. In general, members of the Generation X have a higher preference towards owning a car than millennials.

The urban population in the central age groups (25-34 and 35-44) have the lowest scores for this factor, thus suggesting that these groups do not recognize large importance to owning a car, as long as they can access sufficient mobility services through other channels. However, the rather high scores for this factor among young millennials (a group that is found to have lower car ownership levels) seems to confirm that for many individuals in this group, car ownership is still seen has having a value, even if the current lower car ownership levels might be associated with temporary conditions, such as lower income, student status and lack of employment.

Figure 16 reports the average factor score and confidence interval for the *cars as a tool* factor score. This factor captures the respondents' level of agreement with the statements "The functionality of a car is more important to me than its brand" and "To me, a car is just a way to get from place to place". Also in this case, the lower average factor score for young millennials who live in urban areas seems to suggest that their lower levels of car ownership are only a temporary status.

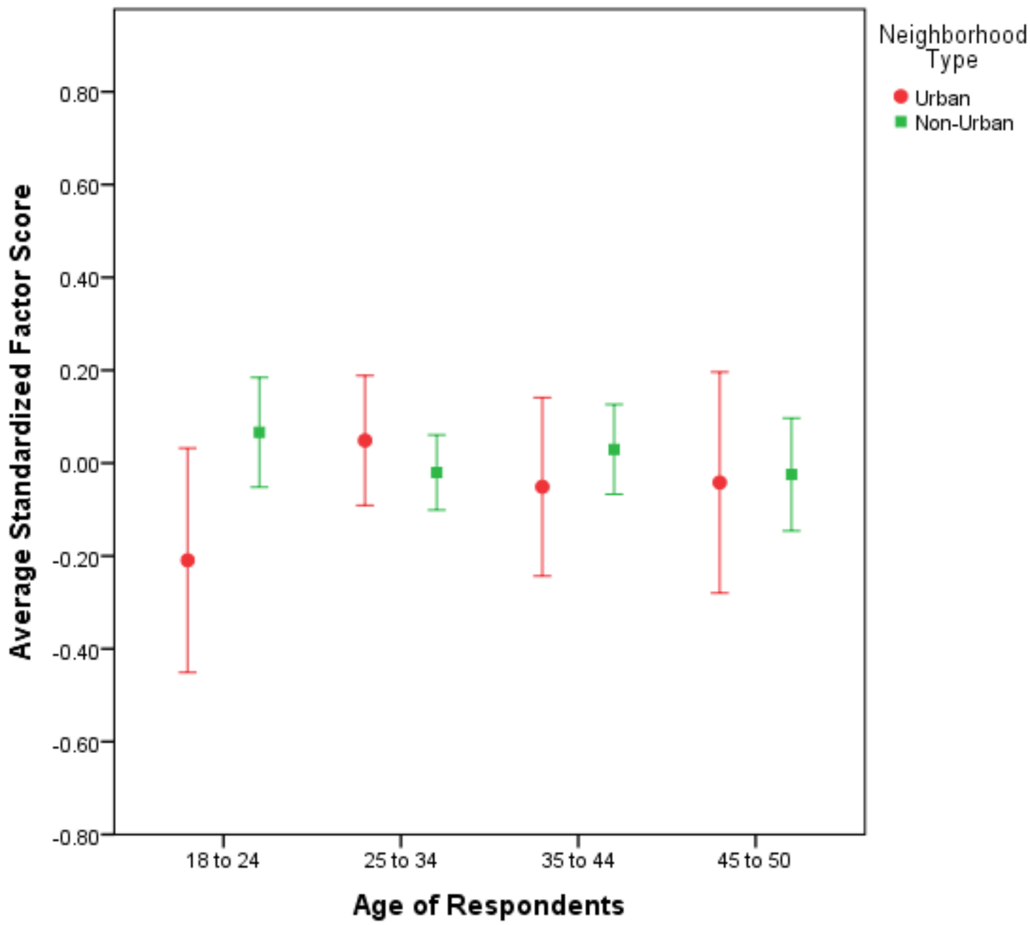

Figure 16. Average "car as a tool" factor score by age and neighborhood type (95% confidence intervals are reported in the figure for each group)

Figure 17 presents the average factor score and confidence interval capturing respondents' inability to use other travel alternatives due to their *time and travel mode constraints* imposed by either their busy schedule or unavailability of different options for traveling. This factor is based on the three attitudinal statements: "My schedule makes it hard or impossible for me to use public transportation," "I am too busy to do many things I'd like to do," and "Most of the time, I have no reasonable alternative to driving".

Among urban residents, older millennials tend to have higher average scores for this factor, while among non-urban residents, the older members of Generation X have the highest average scores. This may be due to physical constraints or other life responsibilities, such as having children.

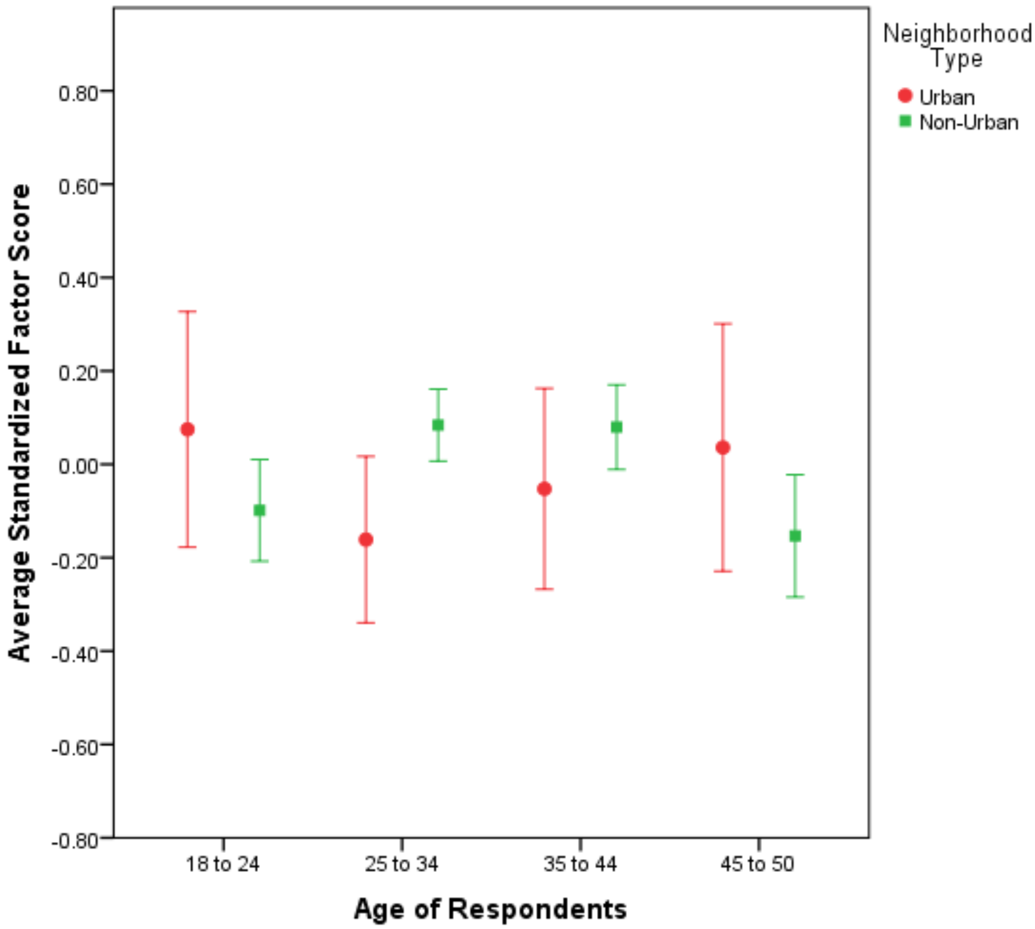

Figure 17. Average time and mode constrain factor score by age and neighborhood type (95% confidence intervals are reported in the figure for each group)

Figure 18 reports the average factor score and confidence interval for the respondents' feelings regarding the adoption of technology. This factor captures the *technological embracement* construct through the statements "Learning how to use new technologies is often frustrating" (with negative sign), "Technology creates at least as many problems as it does solutions" (with negative sign), "Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me" and "Getting around is easier than ever with my smartphone."

Respondents showed a clear pattern with distinctive features between urban and non-urban dwellers. For urban residents, the factor score is positive or close to zero – indicating either positive or neutral feelings about the role of technology across all age groups. For non-urban residents technology excitement decreases with age. Young millennials (18-24) have higher enthusiasm about technology, while old millennials (25-34) have slightly lower propensity towards technology, and the members of Generation X report the lowest embracement of or reliance on technology.

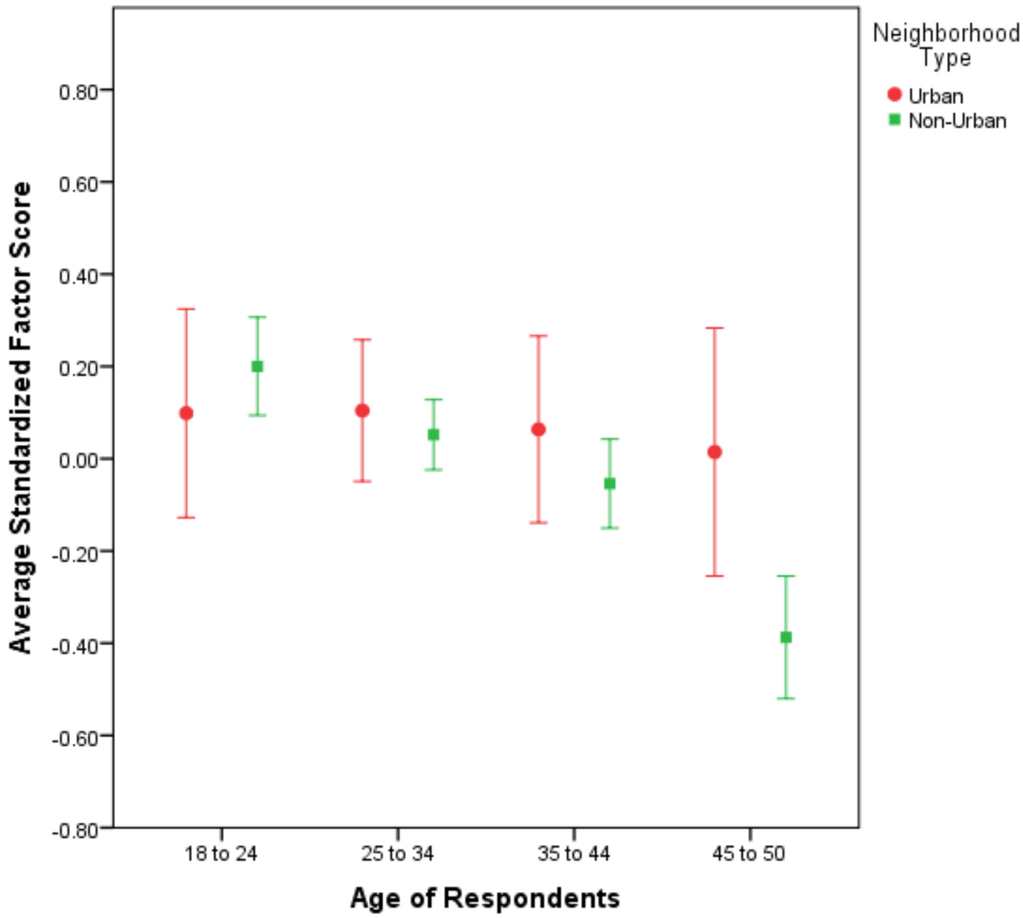

Figure 18. Average "technology embracing" factor score by age and neighborhood type (95% confidence intervals are reported in the figure for each group)

The last factor score that is described in this report is *materialism*. Figure 19 shows the differences in the average score for this factor by age group and neighborhood type. Those that have higher values for this factor tend to agree with the following statements: "I would/do enjoy having a lot of luxury things", "For me, a lot of the fun of having something nice is showing It off", "I like to be among the first people to have the latest technology", "To me, owning a car is a symbol of success". Also, those with high factor scores tend to disagree with the statement: "I prefer to minimize the material goods I possess".

The average scores for this index tend to decrease with the increasing age of the respondents. Young millennials in both urban and non-urban areas have the highest average scores, perhaps due to their interest in having the latest gadgets, or their stage of life – where few have children or mortgages that prevent them from acquiring or wanting to acquire material goods.

Older Generation X members have the lowest average scores for the materialism factor. In future stages of the research, it will be very interesting to explore how the members of the following Generation Z (under 18 year olds, as of today), will behave in future years, compared to these generations that we are studying. In addition, non-urban respondents (apart from the young millennials) tend to have lower average values for this factor, and thus have lower materialistic attitudes, than their urban counterparts.

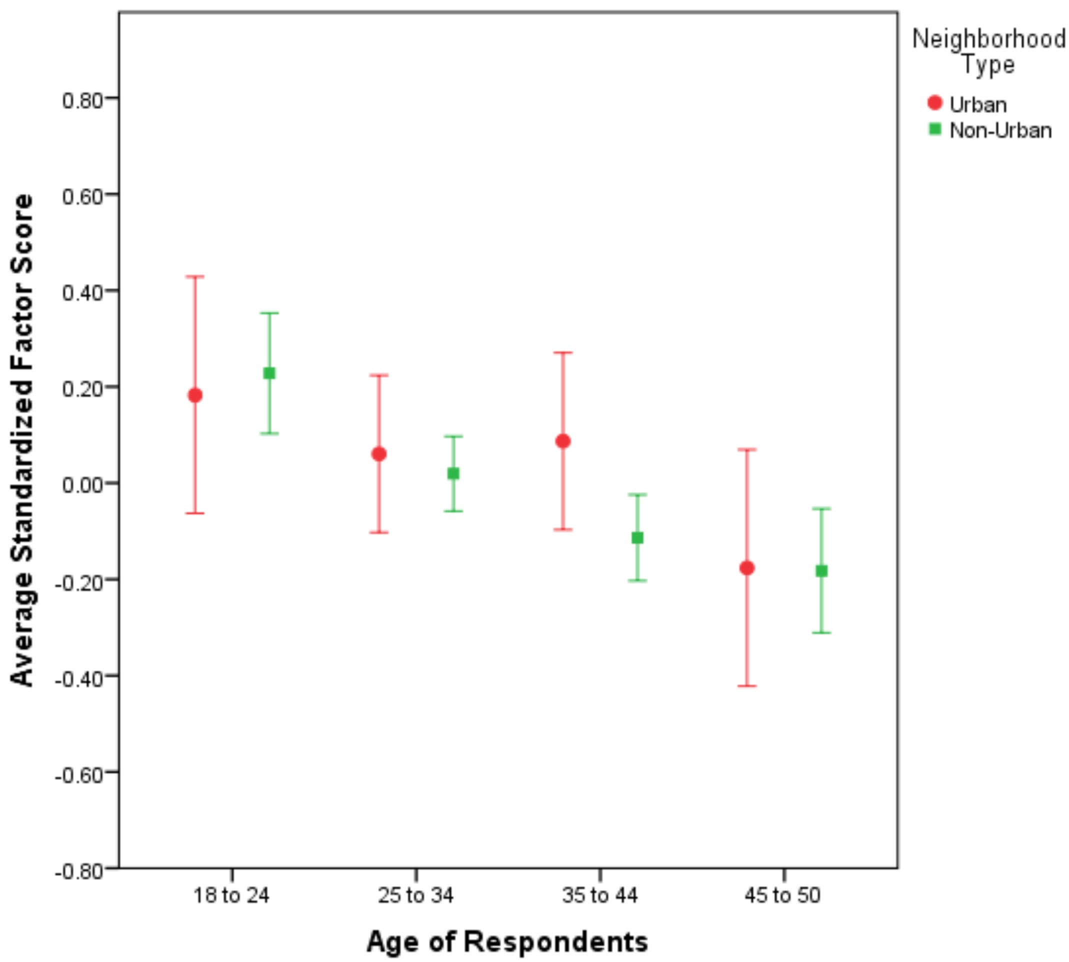

Figure 19. Average "materialism" factor score by age and neighborhood type (95% confidence intervals are reported in the figure for each group)

Travel Behavior and the Accessibility of the Place of Residence

In the Part I report for this research study (Circella et al., 2016b), we discussed a number of observed differences in the travel behavior of millennials vs. the older counterparts belonging to the preceding Generation X. Among the observed differences, the analysis of the collected data highlighted that millennials tend to drive less, and this differences holds even after controlling for the neighborhood type where the respondents live. Further, a larger proportion of millennials report not to have a valid driver's license at the time they completed the survey.

Millennials also are less likely to drive during their commute, and more often use active modes of transportation, including walking and biking, as well as riding public transit. Among the individuals that physically commute to work at least one per week, millennials tend to more frequently engage in travel multitasking (i.e. carry out an activity while traveling) during their commute, compared to Gen Xers in all regions of California. The higher adoption of multitasking, which correlates with the larger adoption of ICT devices among millennials, might be associated with a different evaluation of the utility of travel alternatives, and therefore explain at least in part the observed differences in mode choice.

One of the reasons that may be behind the observed differences in travel patterns between members of the different generation relates to the characteristics of the built environment of the residential location and the work/school location where individuals travel. For example, the following Table 7 and Table 8 respectively report the average frequency of use (by day) of on-demand ride services such as Uber Lyft and of car-sharing services such as Zipcar or Turo.

Table 7. Average Frequency of Use of Uber/Lyft by Generation and Neighborhood Type

	Millennials (N=1157)	**Generation X** (N=998)
Neighborhood Type		
Rural	0.004	0.003
Suburban	0.010	0.007
Urban	0.056	0.039

Note: Numbers in the table measure the average number of per-capita trips per day by neighborhood type (ordinal frequency categories were transformed into discrete numbers of trips to compute the data in this table)

While carsharing services are certainly more rarely used than on-demand ride services such as Uber or Lyft, Tables 7-8 report some similar trends, with residents of denser, more central locations using these services more often than suburban or rural residents. In all these areas, millennials tend to use shared mobility services more often than Gen Xers. Thus, considering also the different distributions of the urban vs. non-urban populations of millennials and older peers, a composite effect might explain the adoption of these trends: not only millennials are more likely to adopt these services than older peers, holding the characteristics of the neighborhood constant, but millennials are also more likely to live in urban areas. The joint decisions of the residential location where an individual decides to live, and the type of travel behavior they have is an important topic to explore in order to investigate the reasons behind, and the impacts of millennials' decision.

Table 8. Average Frequency of Use of Zipcar/Turo by Generation and Neighborhood Type

	Millennials (N=1157)	**Generation X** (N=998)
Neighborhood Type		
Rural	0.00211	0.00010
Suburban	0.00202	0.00070
Urban	0.00984	0.00098

Note: Numbers in the table measure the average number of per-capita trips per day by neighborhood type (ordinal frequency categories were transformed into discrete numbers of trips to compute the data in this table)

To understand the impact of built environmental characteristics, we integrated our dataset with other information using the geocoded self-reported residential location address. Figures 20-22, present the average values of some residential location accessibility measures for the different age group and by different modes. The figures respectively present the average walk score, bike score, and transit score of millennials and generation X by neighborhood type.

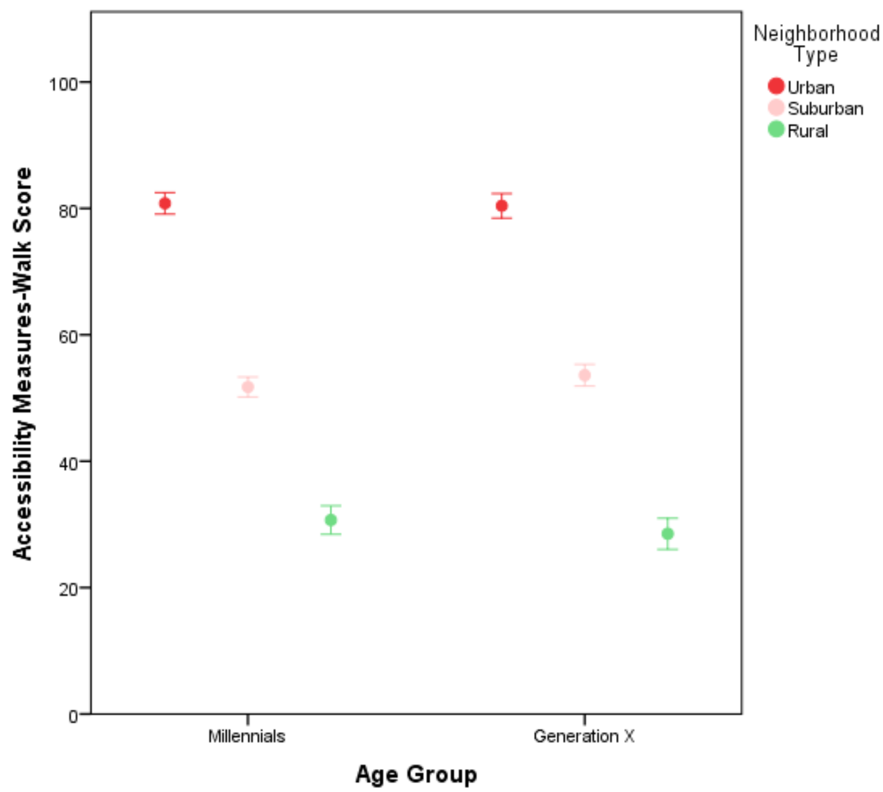

Figure 20. Walk score by age group and neighborhood type

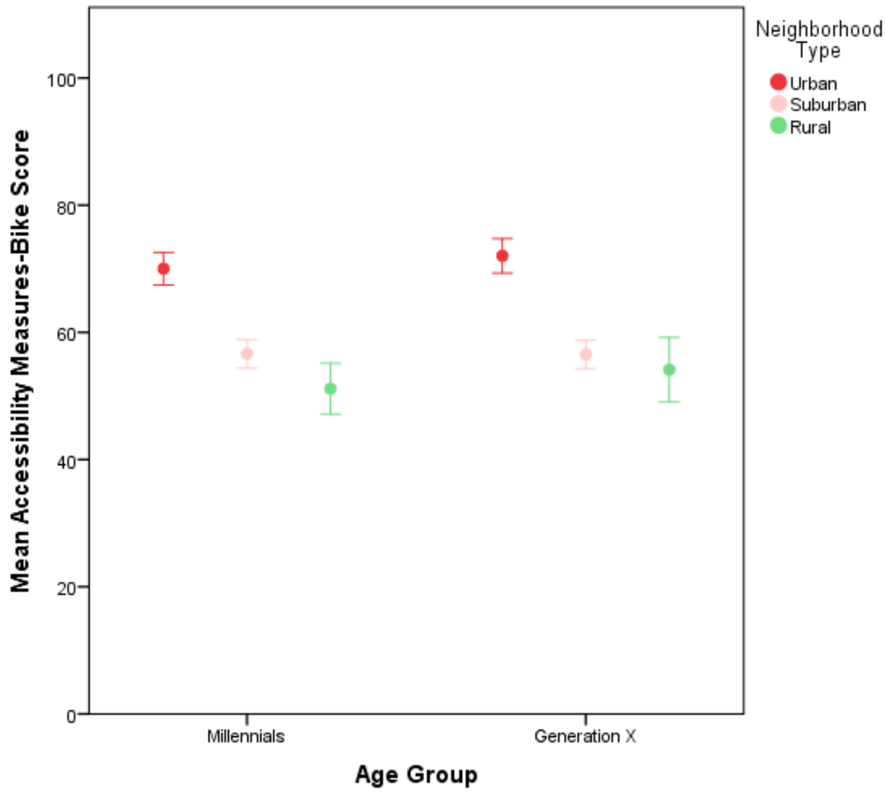

Figure 21. Bike score by age group and neighborhood type

The average scores observed across the residential location of Gen Xers and millennials are very similar within a neighborhood type. For example, the average walk score (Figure 20) for an urban millennial was 80.8, compared to 80.4 for a member of Generation X in an urban area (though more millennials tend to live in such neighborhoods, than Gen Xers). However, large differences in the walk scores are found across neighborhood types: for example, millennials who live in suburban areas have an average walk score of 51.7, compared to average walk score of 30.7 in rural areas.

The differences in the bike scores (Figure 21) were slightly less pronounced, due the more homogenous characteristics of bike accessibility (e.g. many suburban neighborhoods and rural areas are rather bike-friendly), for example with millennials' bike scores ranging from 70 (urban) to 56.7 (suburban) to 51.2 (rural). Transit scores showed a similar pattern, though with a more significant drop in the average scores in rural areas. Urban millennials had an average transit score of 60, while suburban millennials had an average score of 35, and rural millennials had an average score of 22.

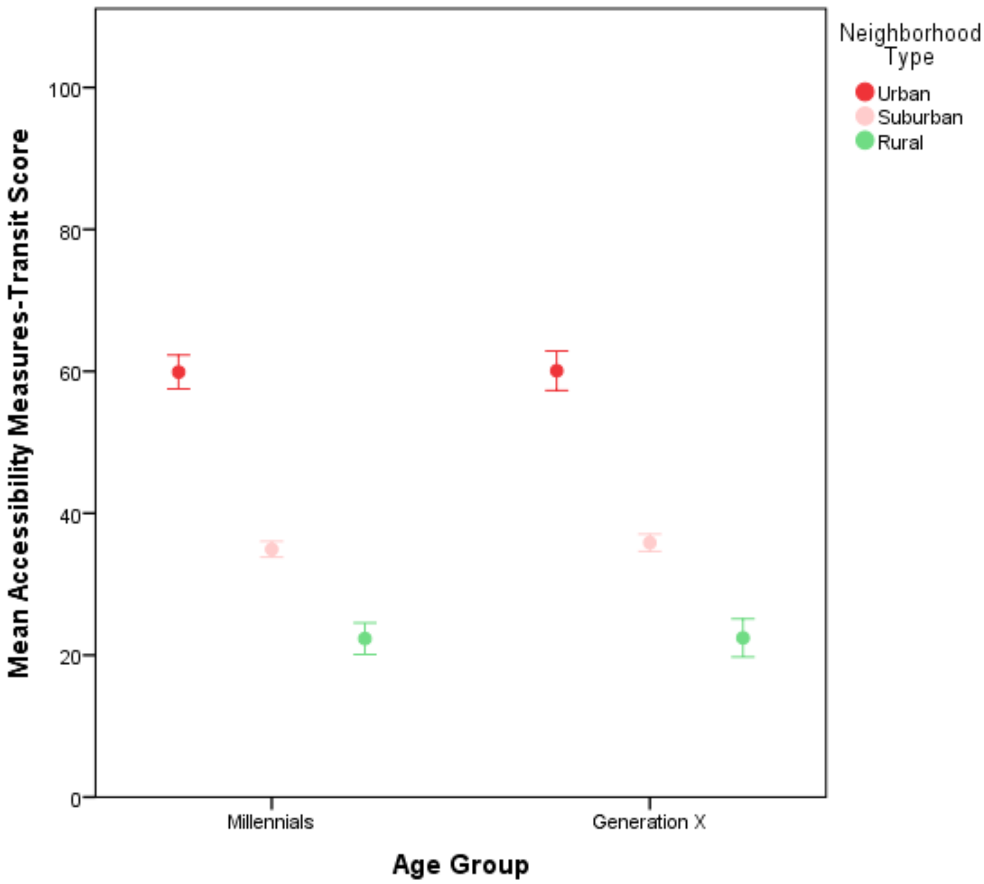

Figure 22. Transit score by age group and neighborhood type

There were no significant differences in the average accessibility measured by these scores between millennials and Generation X, with the only exception of the walk scores for rural millennials which were 2 percentage points higher than those for rural Gen Xers, suggesting that millennials may live in slightly more walkable rural areas. However, for the most part, millennials and Gen Xers have average accessibility scores within a point.

Adoption of Multimodal Travel Behavior

As previously described in this report, in order to enrich the California Millennials Dataset with land use data available from other sources, we develop several measures of accessibility using two main sources of data that were imported based on the geocoded residential location of the respondents: the Smart Location Database (SLD) develop by the US Environmental Protection Agency and Walkscore.com. SLD data provide land use measures on density, diversity, design, access to transit, and destination accessibility at the Census 2010 block group level (Ramsey & Bell, 2014). We complemented these data with the *walk scores*, *bike scores*, and *transit scores* available from the commercial website walkscore.com, which reflect more micro-level built environment characteristics available at a finer level of spatial detail than the census block group and are based on recently updated data sources.[7] For the respondents that provided a valid street address we computed accessibility measures based on the census block group for the SLD measures, and on the latitude and longitude of the residence for the scores obtained from Walkscore.com

In this analysis, we further classified millennials in two groups: the *independent millennials* who do not live with their parents, and the *dependent millennials* who live with their parents. We assume that independent millennials have more flexibility in choosing their residential location, but dependent millennials are affected by their parents in their residential choice and mode choice for various trips. For the respondents that provided a valid street address we computed accessibility measures based on the census block group for the SLD measures, and on the latitude and longitude of the residence for the scores from Walkscore.com.

Further, for each respondent in the dataset, we computed several multimodality indices using information on the mode(s) that the individual used for their last commute tour.[8] We classify respondents based on their mono- vs. multi-modality status as *mono-car* (i.e. individuals who drove alone or carpooled for their entire commute tour), *mono-transit* (i.e. individuals who only used public transportation services such as bus, commuter rail, and light rail for the entirety of their commute tour), *mono-walk* (i.e. individuals who only walked to work or school), *mono-bike* (i.e. individuals who only biked to school or work), and *mono-other* (i.e. individuals that exclusively used other modes of transportation, e.g. on-demand ride services, ferry, etc. for their commute). We also defined two inter-modal indices for individuals who used more than one modes during their commute tour: *intermodal-car* (an index that identifies individuals who used a car as their main commute mode in conjunction with other secondary modes) and *inter-modal green* (that identifies individuals who used any non-car mode as their primary mode of transportation, combined with other secondary modes).

We computed these indices for all respondents that commute to work or school at least once per week, and have a valid geocoded address. The sample available for this analysis consists of 483 independent millennials, 320 dependent millennials, and 584 Gen Xers. Figure 23 reports the summary statistics for the two largest metropolitan areas of California, San Francisco and Los Angeles, comparing the average for four of the eight multimodality indices that were created and the average accessibility measures for the three groups that have been identified.

[7] There are some limitations in the use of the walk score when comparing different neighborhoods: for example, many communities where the homeowners maintain the parks, community centers and other amenities get low scores from Walkscore.com because the facilities are not considered "public", even though anyone who lives anywhere near has access and the communities are not gated. Despite these limitations, the score provides a useful measure of a neighborhood's walkability, with a standardized score that can be easily compared across locations.

[8] Additional measures of multimodality were computed for non-commuting/leisure trips, but are not further discusses in this report, for brevity.

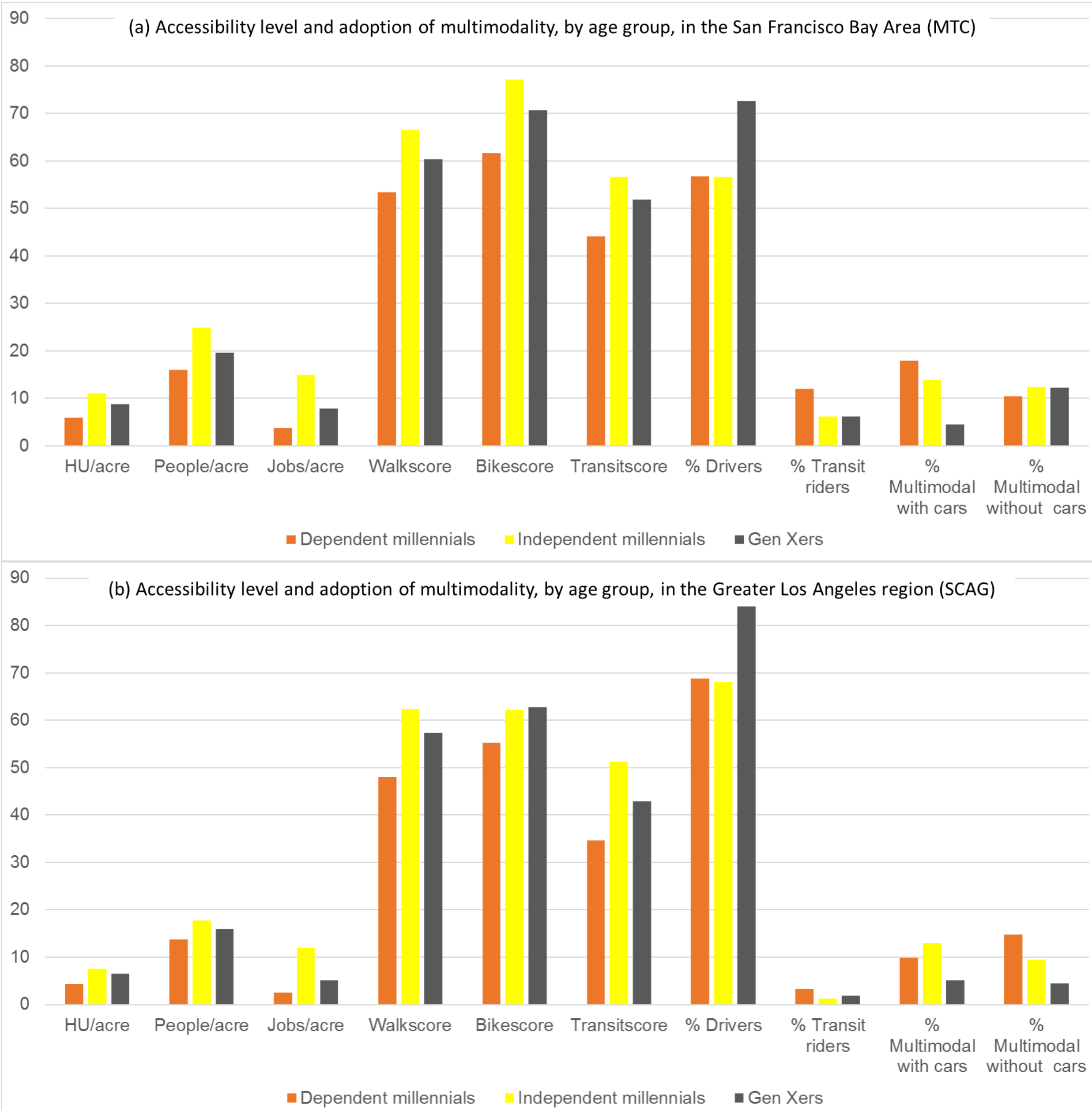

Figure 23. Accessibility level and adoption of multimodality, by generational group, in (a) the San Francisco Bay Area (MTC); and (b) Greater Los Angeles region (SCAG)

In both regions,[9] independent millennials have the highest values for all accessibility measures. Important differences are observed among dependent and independent millennials. Dependent millennials tend to live in areas that have the lowest levels of accessibility by non-car modes,

[9] The trends in both regions are similar, with the only exception that levels of accessibility by non-auto modes are higher in San Francisco/MTC, while the percentage of *mono-car* commuters, in particular among Gen Xers, is higher in Los Angeles/SCAG.

probably due to the residential location chosen by other members of the households (e.g. young adults who still with their parents). Independent millennials, on the other hand, are more often found to live in locations with higher accessibility. Such locations are more conducive to the adoption of *greener* and non-auto commute modes (and/or may reinforce the propensity of young adults to use such modes), as more often done by the individual in this group. At the other end of the spectrum, Gen Xers rely heavily on the use of cars for their commute. Interestingly, in both regions Gen Xers are found to enjoy better travel accessibility than dependent millennials. This seems to signal that at least some dependent millennials tend to drive less and have a more multimodal travel behavior despite living in neighborhoods that are less conducive to multimodality and to the use of non-auto modes. Several explanations could be behind this finding, including the impact of lower income and weaker economic conditions (which constitute potential constraints to millennials' use of private vehicles), reduced family obligations (e.g. millennials who live with their parents are less likely to have their own children to escort to school or extracurricular activities, therefore they have fewer constraints of this type, and more space for individual choices), and/or higher propensity towards such behaviors. Most likely, a combination of these factors is behind these patterns.

Table 9, below, summarizes the accessibility measures and multimodality scores that were computed for the various regions of California. Next, Figure 24 summarizes the adoption of multimodal behavior by region of California and sub-segment of the population.
In summary, accessibility and multimodality are positively correlated: residents of neighborhoods with better accessibility are more often found to be multimodal commuters. However, millennials, and especially dependent millennials, are found to make the most of their built environment potential, either due to individual choices or the presence (or lack) of travel constraints.

They are less likely to be mono-drivers and more likely to be multimodal commuters, even if they live in neighborhoods that are less supportive of such behaviors. This suggests that the connection between the built environment and travel patterns may differ by generation: in future steps of the research we plan to further investigate (and model) the relationships between accessibility and multimodal behavior among the members of the different generations, while controlling for other factors affecting residential and travel choices. Further information can be found in Circella et al. (2017).

Table 9. Average accessibility measures and use of commute modes by region of California and generational group

	Sample size (N)	Housing units/ acre	People/ acre	Jobs/ acre	Walkscore	Bikescore	Transitscore	Always car	Other mode (transit, walking, biking)	More than one mode
Central Valley										
Independent Millennials	73	2.5	7.0	1.4	37.0	53.7	27.8	74.4%	7.3%	18.3%
Dependent Millennials	35	3.0	8.5	2.2	41.0	55.9	30.9	60.0%	22.9%	17.1%
Gen Xers	82	3.2	8.8	2.1	42.7	56.8	29.8	83.6%	9.6%	6.8%
MTC										
Independent Millennials	179	11.1	24.9	14.9	66.6	77.1	56.7	56.6%	17.1%	26.4%
Dependent Millennials	67	5.9	16.0	3.7	53.4	61.7	44.1	56.7%	14.9%	28.4%
Gen Xers	129	8.7	19.6	7.9	60.3	70.7	51.8	72.6%	10.6%	16.8%
Northern California and Rest of State										
Independent Millennials	53	3.5	8.9	2.6	47.6	82.6	32.2	60.4%	18.8%	20.8%
Dependent Millennials	26	2.4	6.8	1.5	30.9	52.3	18.3	80.8%	0.0%	19.2%
Gen Xers	48	2.3	5.6	2.3	36.2	86.2	17.0	81.1%	11.3%	7.5%
SACOG										
Independent Millennials	90	4.1	9.2	3.7	48.8	79.3	32.2	76.8%	13.7%	9.5%
Dependent Millennials	32	3.4	8.8	1.7	41.3	66.0	28.9	68.8%	6.3%	25.0%
Gen Xers	95	3.3	8.3	5.7	42.0	73.8	33.4	82.2%	11.1%	6.7%
SANDAG										
Independent Millennials	114	6.4	14.0	5.2	51.0	50.3	38.4	73.8%	8.4%	17.8%
Dependent Millennials	43	4.5	11.6	2.3	44.2	41.2	33.1	62.8%	7.0%	30.2%
Gen Xers	107	7.0	15.0	7.5	57.7	54.1	41.3	80.7%	5.3%	14.0%
SCAG										
Independent Millennials	156	7.5	17.8	11.9	62.3	62.2	51.3	68.0%	9.5%	22.5%
Dependent Millennials	61	4.4	13.8	2.5	48.0	55.2	34.6	68.9%	6.6%	24.6%
Gen Xers	169	6.6	16.0	5.1	57.3	62.7	42.8	84.0%	6.4%	9.6%
Total										
Independent Millennials	665	6.6	15.2	8.1	54.8	63.6	44.0	68.3%	11.9%	19.8%
Dependent Millennials	264	4.3	12.0	2.5	45.3	54.5	34.8	64.8%	10.2%	25.0%
Gen Xers	630	6.1	14.1	5.8	52.8	62.9	42.0	79.8%	8.7%	11.4%

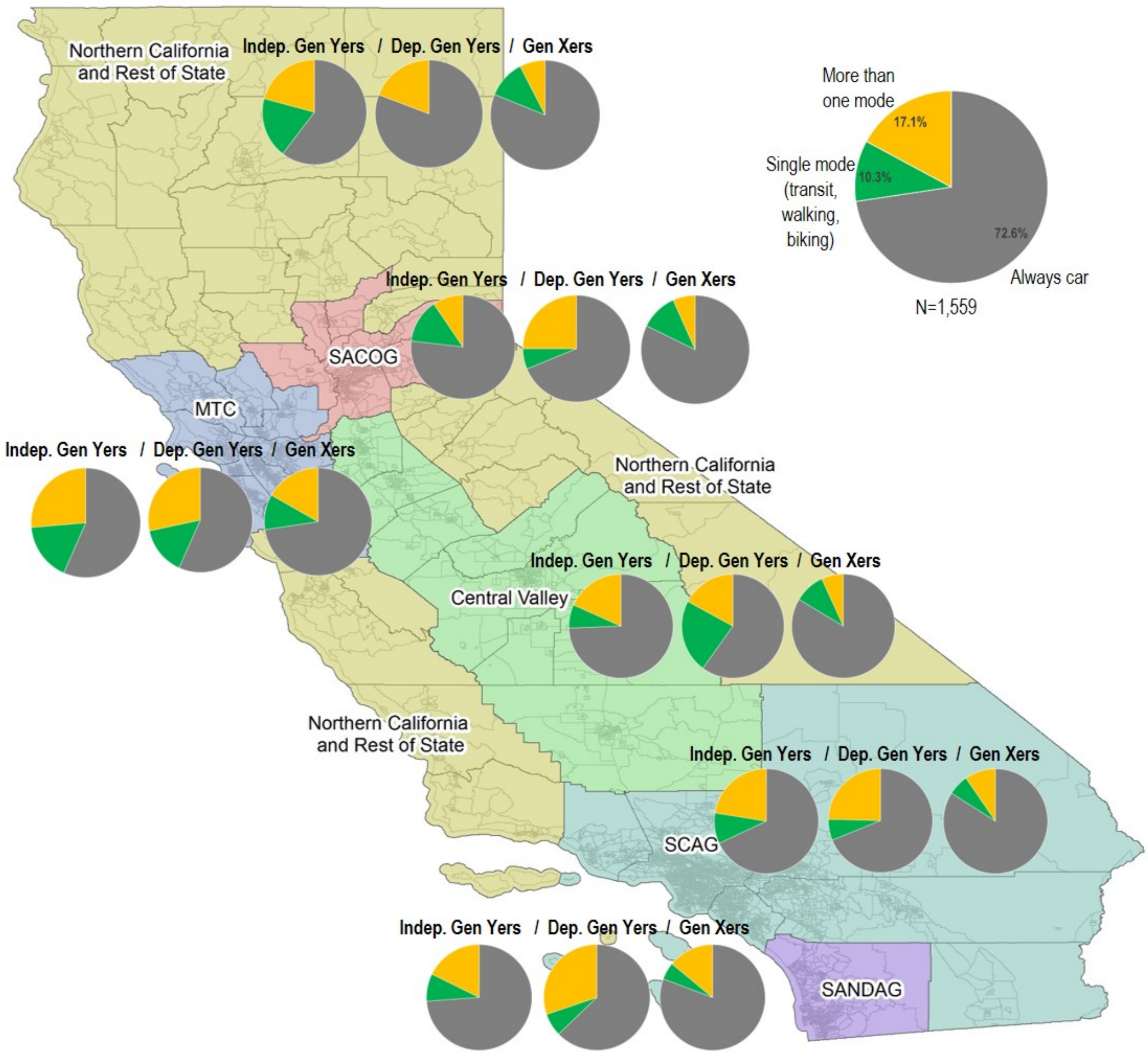

Figure 24. Adoption of multimodal behavior, by region of California and sub-segment of the population

Vehicle Miles Traveled

As pointed out in the literature, millennials may travel differently, and for different reasons, than previous generations. In this section, we investigate the reasons affecting millennials' vehicle miles traveled (VMT) while comparing them with the corresponding patterns observed among the members of the preceding Generation X. As observed in many previous studies, millennials tend to postpone marriage, household creation, and childbearing, and they have fewer total children than previous generations (Pew Research Center 2014; McDonald 2015). All these patterns might contribute to lower VMT. Households without children tend to have lower VMT than those with children (Santos et al. 2011; Le Vine & Jones 2012). However, older millennials may already exhibit patterns similar to older generations, indicating that millennials may "drive later, rather than drive less" (Garikapati et al. 2016).

Surveys of millennials report that the members of this cohort seem to have stronger preference for dense urban areas (Pew Research Center 2014; Polzin et al. 2014; BRS 2013; Zmud et al. 2014), and are more committed to environmental causes (Hanks et al. 2008; Strauss & Howe 2000), which may also contribute to reducing VMT (Ewing & Cervero 2010). The built environment is a strong determinant of VMT: numerous studies have connected population density, employment density, and regional diversity (among other dimensions of the built environment) with vehicle miles traveled. Vehicle miles traveled seems to be most strongly related to measures of accessibility to destinations. More generally, residents of more traditional dense urban neighborhoods tend to drive less than those that live in less dense suburban neighborhoods (Santos et al. 2011; Ewing & Cervero 2001; Cao et al. 2009b; Cervero & Duncan 2003; Cervero & Duncan 2006). However, it is unclear how this effects may affect future travel demand, as millennials age and move to a different stage of life. In other words, the often reported millennials' preference for urban areas and reduced use of personal vehicles might be a temporary trend, associated with their stage in life, and may not be a lasting trend (Myers 2016).

Another well-studied correlate of VMT is virtual mobility or adoption of information communication technology (ICT), which is another factor often indicated as potentially affecting the amount of individuals' travel and mode choice (Mokhtarian 2009; Salomon & Mokhtarian 2008; Contrino & McGuckin 2006, Circella and Mokhtarian, 2017). Millennials are more likely to adopt virtual mobility options, such as online shopping, telecommuting, ride-sharing, and other real-time transportation services (Blumenberg et al. 2012; Zipcar 2013). McDonald (2015) suggested that the millennial use of virtual mobility might explain a significant portion in the drop in driving observed among the members of this generation. More generally, the ubiquity of the smartphone adoption along with increases in mobility options have created a class of "real-time riders" (ITS America 2015) that spans all cohorts. Still, millennials are the first generation of so-called 'digital natives' (Prensky 2001), having grown up with the internet, and are likely to be the users that most benefit from the availability of modern technologies and emerging transportation technologies (including the modern shared mobility services). This may apply to following generations, too, but is only becoming apparent with millennials (Lyons 2014).

It is thus important to study the cohort effects and explore the impact of traditional explanatory variables such as the built environment and socioeconomic factors and their likely effects on the travel behavior of the members of different generations. In this section, we study the self-reported VMT of millennials and Generation X, and investigate the impact of multiple explanatory variables, including sociodemographics, land use characteristics and individuals' attitudes, on the self-reported VMT.

Dependent Variable: Self-Reported Weekly VMT

The following sections present the results of a model that was estimated using the self-reported weekly VMT as the dependent variable. The weekly VMT reported by individuals ranged from 0 to 1000, with a mean of 115 miles per week, and a median of 75. Information for this variable, which is likely to be affected by some limitations typical of any self-reported measures of travel behavior (e.g. eventual under-reporting of trips and VMT) was collected in a similar way for all respondents in the dataset. We used a log-transformation of the VMT variable, in order to reduce the deviation from the normality of the variable. Due to the presence of cases with VMT equal to zero, and in order to avoid taking the logarithm of zero, the final dependent variable that was used in the model was ln(VMT+1), as often done in similar models in the literature.

Explanatory Variables

Sociodemographic

We used several sociodemographic variables in our model. The variables used included both individual and household characteristics. Further, in order to allow non-linear relationships of VMT with age, we also included a quadratic term for the age of the respondent (i.e. "squared age" was also included) in the model. It is expected that vehicle travel increases as adolescents become adults, peaks during adult age (30-60 years) when employment and childrearing responsibilities are greatest, and then declines as individuals retire and age (Le Vine & Jones 2012). We also tested the inclusion of age in segmented models to model the effect of age in each generation: millennials and Generation X.

We included occupation or employment, coded as *student only*, *worker only*, *student and worker*, and *unemployed*. Household income was also included as a determinant of VMT. Previous studies have found that income has a positive effect on VMT (Brownstone & Golob 2009; Rentziou et al. 2012; Greene et al. 1995). In this study, we used three annual household income brackets (respectively, lower than $35,000, $35,000-$100,000, and higher than $100,000) to allow income to have a nonlinear relationship with VMT.

Built environment

Ewing and Cervero (2010) summarizes the findings from the literature regarding the effects of the built environment characteristics on VMT and travel behavior. In this study, we use the geocoded information on the residential location reported by the respondents to match each case with additional information about the local land use characteristics, including the neighborhood type as determined in a previous study developed by researchers at UC Davis (Salon 2015).

Within a census block, characteristics may vary enough that resident neighborhood perceptions and experience may vary (Handy 2002; Handy et al. 2005; Bagley et al. 2002). In addition, not only the objective characteristics of the built environment but also the perceived neighborhood characteristics are found to be good predictors of travel behavior (Handy et al. 2006). In this study, we used gross population density (people/acre), gross employment density (jobs/acre), job diversity, and total road network density as objective measures of the local built environment characteristics. Both population and employment density were previously found to be significant (Cervero & Murakami 2010) in predicting VMT. In addition, we used regional diversity, based on population and total employment, deviation of the ratio of jobs/pop in a census block group from the regional averages, and trip productions and trip attractions equilibrium index. These variables are good measures of the characteristics of the land use. Where these measures are more balanced, the local mix of land uses is thought to reduce travel time and distance (Cervero & Duncan 2006).

Technology Adoption and Use of Social Media

The adoption of information communication technology (ICT) has been often reported as a potential factor affecting travel behavior, which, depending on the local context and individuals' characteristics, may lead to substitution of, generation of, modification of or neutrality with the amount of travel (Salomon and Mokhtarian 2008, Circella and Mokhtarian, 2017). In this study, we controlled for several measures of ICT adoption and use. In the final model, we use a variable that measures the frequency with which the respondents telecommute for their work to account for the potential impacts of telecommuting on weekly VMT.

New mobility services such as Uber and Lyft may function similarly, generating new trips and increasing VMT or replacing driving miles (Taylor et al. 2015; Hallock & Inglis 2015; Shaheen et al. 2015). We created variables to assess the respondent's frequency of using new shared mobility services, including: *on-demand ride services* (e.g. Uber and Lyft), *carsharing* (including fleet-based and peer-to-peer services such as Zipcar, Car2Go and Turo), *bikesharing*, *ridesharing* (including peer-to-peer carpooling and dynamic ridesharing such as Zimride and carpooling that arranged via Facebook or Craigslist). In the study, we transformed the frequencies of use of these services, which were reported as ordinal variables in the survey, into monthly frequencies by assuming that ''5 or more times a week" can be considered 5 times a week (5/7), "3-4 times a week" can be considered three and a half times a week (3.5/7), ''1–2 times a week'' can be considered 1.5 times a week (1.5/7), ''1–3 times a month'' becomes 2 times a month (2/30), "less than once a month" becomes 3 times per year, and "I used it in the past" (but not anymore) is approximated to zero.

Lifestyle Preferences and Individuals' Attitudes

As described in an earlier section of this report, we applied factor analysis as a data reduction technique to analyze the attitudinal variables in the survey and compute 17 factors scores. In the final VMT model, we included the following factor scores:

a. *Established in life*: Individuals who score highly on this factor strongly agreed with statements including "I'm already well-established in my field of work" and they tended to disagree with the statement "I'm still trying to figure out my career (e.g. what I want to do, where I'll end up)."
b. *Preference for suburban neighborhoods* (pro-suburban): Individuals who score highly on this factor tended to agree with the statements that emphasized the preference for living in spacious homes that were further away from public transit and living in a location with large yards and lots of space between homes.
c. *Responsiveness to the environmental impacts and price of travel*: Individuals who score highly on this factor tended to agree with the statements "The environmental impacts of the various means of transportation affect the choices I make", "I am committed to using a less polluting means of transportation as much as possible", "The price of fuel affects the choices I make about my daily travel" and "To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle". This factor captures respondents' willingness to change travel plans based on both gas prices and environmental concerns.
d. "*Must own a car*": Individuals who score highly on this factor agreed with "I definitely want to own a car" and disagreed with the statement "I am fine with not owning a car, as long as I can use or rent one any time I need it".
e. *Time/mode constrain*: This factor captures the attitude of respondents who more likely drive by necessity as opposed to by choice. This is the amalgamation of four attitudinal statements. Those that loaded positively onto this factor tended to agree with the following statements "My schedule makes it hard or impossible for me to use public transportation," "I am too busy to do many things I'd like to do," and "Most of the time, I have no reasonable alternative to driving". Respondents who scored high on this factor may have no reasonable alternative to driving. This factor is likely strongly correlated with the built environment characteristics and neighborhood type where the respondents live.

Results

We estimated weighted log-linear models using the log-transformation of the self-reported measure of weekly VMT as the dependent variable. Table 10 summarizes the estimated coefficients for a pooled model, which includes both millennials and the members of

Generation X (N = 1801), and the separate models for millennials (N=976) and Generation X (N=825).

All models have very satisfactory goodness of fit, with R-Squared between 0.448 and 0.517 (adjusted R-Squared between 0.439 and 0.509). Therefore, the models are able to explain approximately 50% of the variance of the dependent variable, a value that is remarkable considering the many sources of potential noise that affect individuals' VMT and that cannot be usually captured in econometric models. Interestingly, the millennials' model has the lowest goodness of fit (R-squared of 0.448, compared to 0.517 for the Generation X's model). This confirms the larger heterogeneity in millennials' mobility choices, and the increased difficulty of predicting their behaviors. In other words, while it is easier to predict Gen Xers' weekly VMT, using the rich set of variables available for this research. More sources of noise (e.g. impact of unobserved variables, and/or differences in individual tastes, habits, etc.) characterize the millennials' group. Still, our model does a remarkable job in explaining the variation in millennials' VMT, due to the abundance of variables, such as land use characteristics, individual attitudes, and adoption of technology, which are not available in other datasets. The following sub-sections discuss the impacts of the various groups of variables that were controlled for in the VMT models.

Table 10. Results of the Pooled and Segmented Model of log(VMT+1)

	Pooled Model		Millennials		Generation X	
	B	p	B	p	B	p
(Intercept)	0.487	0.302	-5.253	**<.001**	1.162	**<.001**
Occupation						
Student Only	0.437	**0.004**	0.818	**<.001**	-0.441	0.155
Student and Worker	0.73	**<.001**	0.839	**<.001**	0.608	**0.001**
Works Only	0.687	**<.001**	0.742	**<.001**	0.711	**<.001**
Sex (Male)	0.271	**<.001**	0.205	**0.014**	0.305	**<.001**
Age	0.038	0.163	0.453	**<.001**		
Age^2	-0.001	0.138	-0.008	**<.001**		
Household Income						
>$100k	0.291	**<.001**	0.462	**<.001**	0.342	**0.004**
$35k-100k	0.155	**0.031**	0.194	**0.042**	0.21	0.062
Lives with Parents	-0.235	**0.003**	-0.176	0.083	-0.383	**0.004**
Lives with Children	0.206	**0.001**	0.314	**0.001**		
Car Availability (%)	0.027	**<.001**	0.026	**<.001**	0.029	**<.001**
Telecommuting Frequency	-0.506	**0.001**			-0.693	**<.001**
Population Density	-0.007	**<.001**			-0.013	**<.001**
Diversity	-0.557	**<.001**	-0.325	0.072	-0.9	**<.001**
FS pro-suburban	0.054	0.064			0.066	0.085
FS responsive_env_price	-0.055	**0.047**				
FS established_in_life	0.107	**0.001**	0.091	0.057	0.066	0.122

FS must_own_car	0.106	**<.001**	0.119	**0.003**	0.073	0.082
FS time_mode_constrain	0.165	**<.001**	0.153	**<.001**		
Uber/Lyft Frequency			-1.407	0.05		
Observations	1801		976		825	
R2 / adj. R2	.480 / .474		.448 / .439		.517 / .509	

Socio-demographics

In our pooled model, as well as in the segmented models, variables such as household income, gender, presence of own children in the household, and occupation/employment status were all found to have a statistically significant effect on an individual's VMT. Interestingly, the effects of age (which is controlled for through the use of both the Age variable, and the quadratic term Age^2, to control for non-linear effects of age on the amount of car travel) are found to be significant in the pooled model and in the millennial model only. The findings confirm the assumption that the relationship between VMT and age does not follow a linear relationship. In particular, the estimated model coefficients predict that (after controlling for the effects of other variables, such as HH income, presence of children, etc.) the effects of age on VMT appear to peak at age 35. Similarly, when separating the two segments of the population in the dataset, both the Age and Age^2 terms are not significant in the Generation X model, suggesting that the remaining differences in VMT attributable to age among this group are negligible (i.e. for individuals in the age group 35-50, individual VMT has already "peaked", and the remaining changes in VMT are explained through the impact of other variables).

Across all models, male respondents had higher VMTs than female respondents, though the effect was much smaller in the millennial model. In the pooled model, men drove 30% more miles per week than women, all else equal, while in the millennial model, men drove 24% more miles than women. Among the members of Generation X, men drove 33% more than women. This may indicate that gender differences are smaller within the millennial generation, as women have saturated the workforce (and there are smaller gender differences in lifestyles, income, etc.) and men share in more household obligations. For the millennial model, individuals that were both employed and students had higher VMTs than individuals that worked only, or were students – going to both work and school, assuming that they are in different locations, results in a higher VMT. In the Generation X model, those with the highest VMTs only worked and were not students.

Household composition is found to be a very important factor affecting the amount of individuals' car travel. In particular, individuals that live with their parents tend to drive fewer miles per week than those that have already established their own household. Very interestingly, the presence of children in the household is found to be a very important predictor of VMT for millennials: young adults that have their own children tend to drive more (starting from a lower baseline value for their generation, compared to the older Gen Xers) to a very remarkable extent. The effect of having their own children living in the household is also found to have a significant effect in the pooled model, but is not found to be a significant predictor of VMT for the members of the Generation X.

Car availability (measured as the percent of time a car is available to the individual) was always found to be positively correlated with vehicle miles traveled. In the pooled model, for each additional percent increment of car availability there is a 3% increase in VMT. This variable was used in place of the typical cars per household or cars per licensed driver as a more precise estimate of vehicle availability.

Built Environment

The estimated coefficients indicate that, as expected, population density is negatively correlated with vehicle miles traveled in both the pooled model and Generation X model. This is consistent with earlier findings in the literature (Ewing & Cervero 2001). In the pooled model the effect of density is a small, but significant: an increase in a unit of population density, reported in population per acre per census block, results in a decrease in VMT of 0.07%. However, this variable was not found to be significant in the millennials model. Regional diversity, measured as the census block group deviation from jobs to population ratio from the region's, was negatively correlated with VMT across all models. For example, in the pooled model, a unit increase in regional diversity resulted in a VMT decrease of 43%. This variable has even larger effects among Generation X. Overall, the impact of land use characteristics appears to be larger among the older group. Millennials' VMT seem to be affected to a larger degree by other groups of variables that were controlled for in the model.

Technology Adoption

We controlled for the adoption of technology through several variables in the model estimation. In the final model, we include a variable that accounts for the effect of the frequency of telecommuting (for the individuals that either work or work and go to school), which was found (not surprisingly) to have a statistically significant, and negative, effect on VMT in both the pooled and the Generation X models. Very interestingly, the frequency of telecommuting was not found to be significant in the VMT model for millennials. Whether millennials adopt telecommuting or not, this does not seem to have a significant effect on VMT, perhaps because of the potential substitution of commute trips with car trips done for other reasons.

We also controlled for the impact of the adoption of new shared mobility services. In particular, in the final model, we included a variable that accounted for the frequency of use of on-demand ride services such as those provided by Uber or Lyft. The frequency of use of these services was found to have a significant (at a 0.10 level of significance) and negative effect on millennials' VMT. This suggests that millennials who use on demand ride services tend to drive less. The direction of causality of this finding is unclear though: the adoption of on-demand ride services might lead some millennials to drive less (as a consequence of the adoption of these services, and/or the substitution of trips that would have been otherwise made by driving their car), or the reverse might be also true: millennials that have lower access to a private vehicle (e.g. they live in zero- or low-vehicle-owning households) might adopt these services more often, as a way to compensate for their lower auto accessibility. This topic will be further investigated in future extensions of the research, through the application of latent class analysis and the estimation of latent class models to analyze different behaviors among different groups of users, and the estimation of bivariate models that can jointly estimate an individual's amount of car travel (e.g. VMT, or the frequency of use of public transportation) and the frequency of use of modern shared mobility services (including on-demand ride services, such as Uber and Lyft).

Personal Attitudes and Preferences

We used several factor scores that were computed in the factor analysis of attitudinal variables, to control for the impact of individual attitudes and preferences on the individual's amount of car travel. In particular, the factor scores measuring the individuals' perceived lack of alternatives to driving, their degree of responsiveness to the environmental effects and price of travel options, the degree they feel they are well established in life, the preference to own a car (vs. accessing one when needed), and the preference for suburban neighborhoods were found to have significant effects and were included in the final pooled model (and in several cases also in the segmented models).

All attitudinal factor scores were found to have an important effect in explaining individual VMT. Individuals that reported that they do not have reasonable alternative to driving were found to report higher VMT. Further, VMT was found also to increase with the degree by which a respondent feels established in life (a one-unit increase in this factor resulted in an 11% increase in VMT). These individuals likely have more responsibilities, have higher socioeconomic status and are better established in their careers, resulting in higher VMT. For millennials, in particular, those that have a unit higher score for this variable drive 9.5% more, while this variable is not significant in the Generation X model.

Attitudes were important to control for as a proxy for residential self-selection, which is often a confounding factor in the relationship with VMT and structural variables. Interestingly, the factor score measuring the degree by which a respondent is responsive to the environment effects and price of travel options was found to be significant only in the pooled model (with the expected sign). The weak significance of this variable may indicate that considering the environment effects of travel options when choosing on whether to drive might not have sizable effects on one's VMT, or that this effect is already captured by another variable, such as residential selection or car availability, or choosing to own a car in general.

Those who like cars and definitely want to own one are more likely to have higher VMTs than those who do not load positively on to that factor – the impact of this variable is larger for millennials (and is not found to be significant in the Generation X model). Similarly, the factor score for the pro-suburban attitude was positively correlated with VMT in the pooled and in the Generation X model. An increase of one unit in this factor score (being more "pro suburbs") is associated with an increase of 5.8% in VMT. The full analysis can be found in Tiedeman et al. (2017).

Car Ownership, Vehicle Type Choice and Propensity to Change Vehicle Ownership

More than 17.4 million vehicles were sold in the United States in 2015, breaking the previous record of 17.3 million vehicles sold in 2000 (Harwell and Mufson 2016). The recent increase in car sales has prompted speculations on whether the car market has definitely rebounded after the temporary decrease in car sales during the years of economic recession,[10] though a certain "delay" effect might also be behind the record volumes of car sales in 2015: vehicles sales during the year might have been grown also because many consumers postponed the time of replacement of their vehicles during the economic crisis.

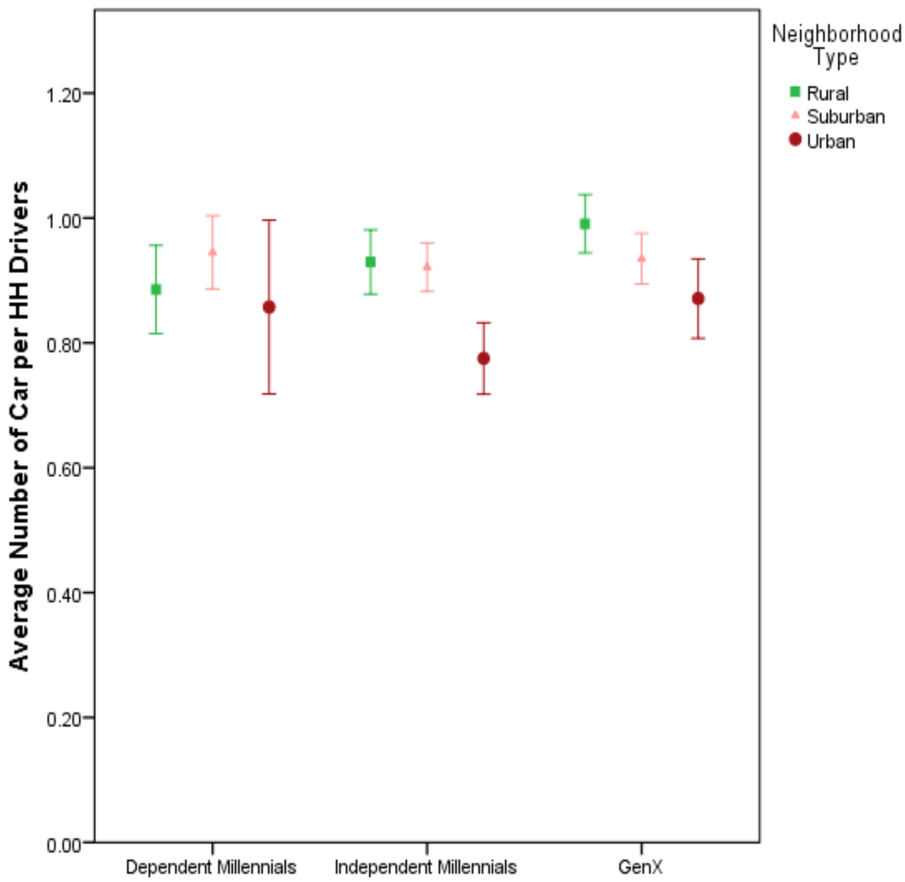

Figure 25. Average ratio of available cars (including minivans, SUVs, pickup trucks) per household member with a driver's license

[10] The discussion about the apparent "peak" in car sales observed during the past few years has also been connected with the observed peak in car travel that was observed during the early 2000s. For a more complete discussion of the factors associated with the observed changes in passenger travel trends in the U.S. see Circella et al. (2016b).

Several factors affect vehicle ownership rate, such as individual and household characteristics, availability and accessibility of different modes of transportation, the quality of travel offered by car vs. the other alternatives, characteristics of built environment, individual's lifestyles and personal attitudes and preferences towards the use of cars and/or other modes. In this section, we first look at two different measures of car ownership using the data available for this project: (1) average ratio of available cars (including minivans, SUVs, pickup trucks) per household member with driving license, and (2) average ratio of available vehicles to household members. We then develop a model of vehicle type choice and analyze the factors that affect the decision on what vehicle to own.

Figure 25 presents the distribution of the ratio of cars per household members with a driver's license by age group and neighborhood type. As discussed earlier, millennials who live with parents are expected to behave differently compared to millennials who do not live with their parents and they have already established their independent household. As shown in the graph, except dependent millennials who live in suburban areas, the average number of vehicles per household driver decreases from rural neighborhood to suburban and urban areas. This could be due to higher availability and accessibility of different travel alternatives and higher cost of car ownership in urban areas. Further, and more interesting, the ratio of vehicles per drivers is sensibly lower for one category: the independent millennials who live in urban areas have the lowest ratio of car per household drivers. This group of individuals is the only one that has an average ratio of cars per household drivers that is lower than 0.8. In contrast, all groups of Gen Xers have much higher ratios of vehicles per household drivers (which for rural Gen Xers is approximately equal to 1).

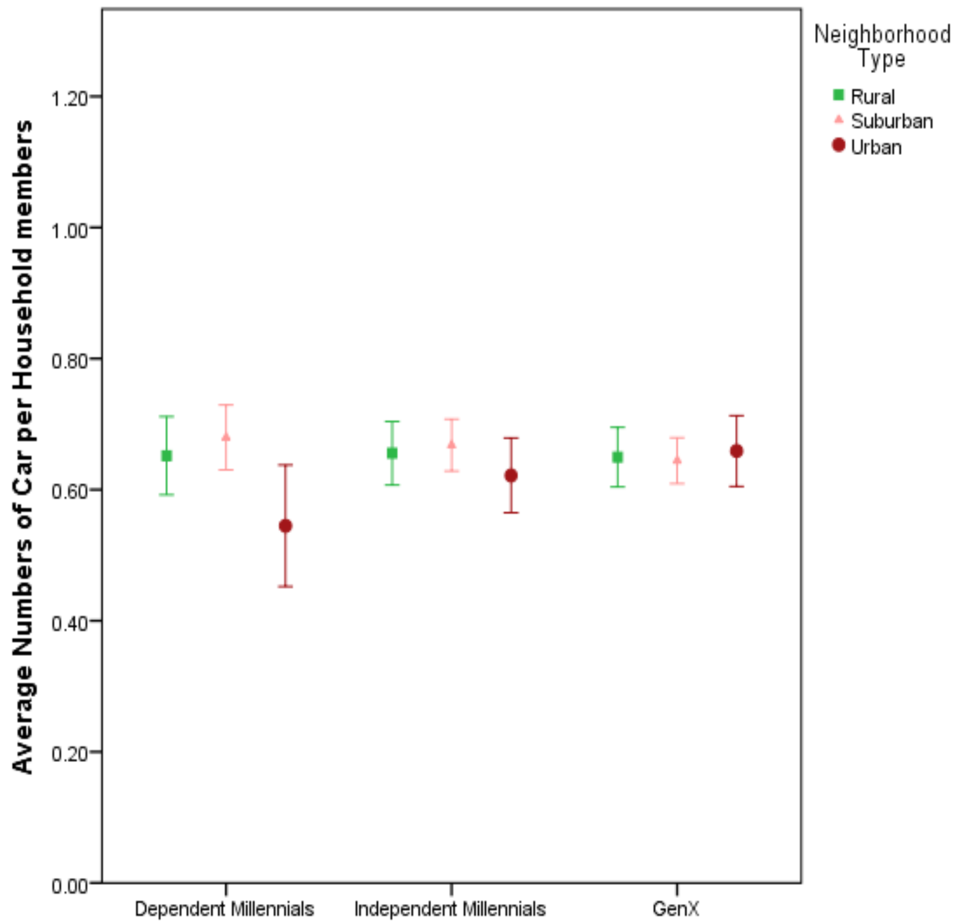

Figure 26. Average ratio of available cars (including minivans, SUVs, pickup trucks) per household member

In contrast to the ratio of cars per household drivers, the ratio of cars per household members (Figure 26) varies in a small range across all different age groups and neighborhood types. The result indicates that both dependent and independent millennials who live in urban neighborhoods have lower car availability compared to their peers who live in rural and suburban areas. In this case, the lower ratio of cars/household members is observed among dependent millennials.

During future stages of the research, we do plan to study how car ownership varies across different groups of the population: the research team is currently working at the estimation of car ownership models that investigate how various sociodemographic characteristics, individual preferences, and land use features affect household car ownership.

Further, an important focus of the research has been focused on what affects the type of vehicles that individuals (and the households in which they live) prefer to own. With cheaper gas and a stronger economy, consumers are flocking to new and used car lots looking for their new car. Recent trends have also shown a resurgence in vehicle sales for larger vehicles (including SUVs, crossovers and pick-up trucks). In this part, we examine individuals who own at least one vehicle in the household, in order to better understand how individual attitudes, lifestyles, built environment characteristics, and socio-demographic traits affect the type of vehicle they own.

As already mentioned, the recent trends in car sales somehow contrast the observed trends in vehicle use and sales from the past few years, which showed an apparent peak in car ownership and use in the United States as well as other developed countries (Schoettle and Sivak 2013; Kuhnimhof, Armoogum, et al. 2012). This trend has been even stronger among young adults, or millennials. Several studies have reported that young adults tend to delay driving licensure, own fewer or no vehicles, and drive less even when they have access to a car in the household (McDonald 2015; Polzin, Chu, and Godfrey 2014; Blumenberg et al. 2012). However, to date, there have been no studies that specifically focused on investigating the vehicle ownership and vehicle type choice among young adults. A larger variety of vehicle types, including sedan, hatchback, two-seater, pick-up truck, SUV, minivan, coupe, etc. are nowadays available on the market. However, rather limited knowledge exists on the motivations affecting buyers of these vehicles, beyond the impact of purchase price and vehicle characteristics such as number of seats, operating costs, etc. Our study aims to contribute closing this gap by investigating the effects of individual attitudes and preferences, generational differences, and individual characteristics on vehicle type choice. Very few authors, to date, have investigated the impacts of attitudes and preferences on vehicle type choice (Baltas and Saridakis 2013; Choo and Mokhtarian 2004). Furthermore, no study has so far looked at generational differences in vehicle type choice.

Since the 1980s, researchers have been examining vehicle type choice (Beggs and Cardell 1980; Berkovec and Rust 1985; Manski and Sherman 1980; Lave and Train 1979). In order to model vehicle type choice, studies typically use either multinomial logit (MNL) (Choo and Mokhtarian 2004; Kitamura et al. 2000; Lave and Train 1979; Manski and Sherman 1980; Fred Mannering and Winston 1985) or nested logit models (Berkovec and Rust 1985; F. Mannering, Winston, and Starkey 2002). Lave and Train (1979) used MNL to investigate the vehicle type purchased and found that larger households that have two or more vehicles are more likely to choose smaller cars (Lave and Train 1979). Moreover, they found that older people and households with high VMT tend to choose larger vehicles. Unsurprisingly, vehicle price negatively affects the choice of each type of vehicle (Lave and Train 1979). Manski and Sherman (1980) were the first researchers to try to model the number of vehicles and vehicle type choice simultaneously (Manski and Sherman 1980). In estimating an MNL model, the authors found that seating and luggage space positively affect the vehicle type choice, and in particular larger one-vehicle households and households with low income are less likely to choose vehicles with higher operating costs (Manski and Sherman 1980). Similarly, Mannering and Winston (1985) developed a multinomial logit model to model the choice among 10 vehicle type alternatives based on year, make, and model (Fred Mannering and Winston 1985). They found that brand loyalty has a significant effect on the choice of the household's vehicle make. Similar to the findings of Lave and Train (1979), vehicle purchase price and operating expenditures negatively affect the choice of a vehicle type (Fred Mannering and Winston 1985). Kitamura et al. (2000) used a multinomial logit model to investigate the choice of vehicle body type (e.g. 4-door sedan, 2-door coupe, etc.) and found that males are more likely to use pick-up trucks, and younger individuals were more likely to use SUVs, pick-up trucks, and sports cars (Kitamura et al. 2000). Unsurprisingly, larger households are more likely to use vans or wagons as these types of vehicles have larger space and seating capacity (Kitamura et al. 2000).

Even though several researchers have explored the factors affecting a household's vehicle type choice, the literature is more limited regarding the impact of individual attitudes, preferences, and lifestyles on this choice. Among the studies that investigated the impact of attitudinal variables on vehicle choice, Choo and Mokhtarian (2004) found that travel attitudes, personality traits, and lifestyles have significant effects on the vehicle type choice (Choo and Mokhtarian 2004). More specifically, people who live in high density areas are more likely to drive more expensive cars, such as luxury and luxury SUVs (Choo and Mokhtarian 2004), and a dislike of travel is positively associated with driving a luxury vehicle (Choo and Mokhtarian 2004). Baltas and Saridakis (2013) developed a multinomial logit model to model the choice of 12 mutually exclusive vehicle type alternatives (Baltas and Saridakis 2013). They were the first researchers to demonstrate that the purpose of car use, the consumer's involvement with cars, and the consumer's attachment to cars, have significant effects on car type choice. Further, their model showed that the propensity to purchase a small car is statistically related to their reliance on friends and family members for advice. Similar to the findings of Choo and Mokhtarian (2004), Baltas and Saridakis (2013) found that those who prefer luxury vehicles are more likely to live in urban areas. Despite the recent interest of the literature in investigating the behavior of the millennial generation, to our knowledge, no previous work has been done investigating the vehicle type choice of young adults.

Vehicle Type Choice Model

For this analysis, we estimated a multinomial logit model (MNL) to explore the relationship among vehicle type choice (the dependent variable in the model) and socio-demographic characteristics, residential location and land use characteristics, and personal attitudes and preferences. We used only a subset of the data in estimating this model, for a number of reasons. First, we restricted the analyses to the individuals who indicated that there was at least one vehicle in the household and provided valid year, make, and model information for the primary household vehicle. Second, in order to focus on the respondents that currently own a vehicle that was purchased by them under conditions rather similar to their current living conditions, and remove the possible bias of respondents who were gifted cars from other family members or purchased an old car out of contingencies (e.g. it was one of the few available in a limited price range) rather than choosing it based on personal preferences and tastes, we narrowed the subset of analysis to the individuals who owned or leased a used or new vehicle that is model year 2010 or newer.

Dependent Variable: Vehicle Type

Survey respondents who indicated that there was at least one vehicle in the household were asked a question about the year, make, and model of the vehicle that they use most. To assign each vehicle to a vehicle type, we used the Environmental Protection Agency's (EPA) Fuel Economy Dataset which provides vehicle classification data for all consumer vehicles from 1984 to the present (EPA 2016). We matched each complete year, make, and model, with a corresponding vehicle classification based on the information provided by the EPA dataset. By using the vehicle's model year, we were able to take into account model redesigns that in some cases moved vehicles from one vehicle type to another. For example, the 1984 Honda Accord is classified in the EPA dataset as a subcompact car but the 2016 Honda Accord is classified as a midsize car[11]. The EPA has more than 15 different vehicle types when accounting for the different drive train options. As we do not have information about the trim level or drive train of the vehicle model in our survey, we aggregated some vehicle types such as Sport Utility Vehicle 2WD and Sport Utility Vehicle 4WD in just one category regardless of the specific trim level or drive train that each vehicle has.

For this analysis we used six different vehicle type choices:

1. Small/compact
2. Midsize
3. Large
4. Luxury
5. SUV
6. Luxury SUV

We excluded "pick-up" trucks and "sport cars" from the analysis due to the small number of pick-up trucks and sport cars owned by the respondents in our sample, and the very different characteristics of these vehicles, which would have significantly increased the heterogeneity of any one vehicle classification (if the vehicles were included in that category). A small number of respondents the dataset reported that they own several vehicles that can be classified as "crossovers" or "minivans". These vehicles were merged in the SUV category, due to the similar size of these vehicles, and the many similarities and overlaps among the vehicles that belong to these categories.

Sociodemographics

We included individual and household socio-demographic and socio-economic characteristics as explanatory variables. We controlled for age through the use of the "age" variable. To control for the non-linearity of age in this model, we also included an "age-squared" variable. We also controlled for household composition through several variables including the number of children and adults in the household. Households with children are expected to more likely

[11] Please note that only model year 2010 or newer were included in the analysis of this paper. The example presented here is only for explanatory purposes on the process that was used in the research

own larger vehicles, vans and SUVs (the last two categories are merged under “SUV” in this analysis) due to their increased seating capacity and comfort for riders.

Finally, as customary in models of this type, we controlled for the impact of other socio-demographic variables such as gender and household income (expecting household income to be an important driver for the purchase of larger and more expensive/luxury vehicles).

Residential Location and Land Use Characteristics

In addition to controlling for the traditional socio-demographic and socio-economic variables, we also controlled for the characteristics of the residential location through the use of an interaction term, which allowed the impact of the annual household income to vary for the households that live in urban neighborhoods (using the non-urban HHs as the reference category). We expected that, holding all else equal, those who live in urban neighborhoods would be more likely to own small/compact vehicles and less likely to own SUVs.

Individual Preferences and Attitudes

As previously described, the survey included 66 separate statements that were included in the study to measure the individual’s attitudes about a number of dimensions related to the environment, travel, adoption of technology, multi-tasking, life satisfaction, land use, the role of government, etc. from which we extracted 17 attitudinal factors. We included three factor scores as explanatory variables in the final vehicle type choice model:

a. *Utilitarian car use* (car as a tool): Individuals who score high on this factor tended to agree with statements such as “The functionality of a car is more important to me than its brand”.
b. *Established in life*: Individuals who score highly on this factor strongly agreed with statements including “I’m already well-established in my field of work” They tended to disagree with the statement: “I’m still trying to figure out my career (e.g. what I want to do, where I’ll end up).”
c. Individuals with multiple transportation modes available and no time restraints (Reversed *time/mode constrained*). This captures respondents that feel as though they have multiple transportation options available to them and are not constrained by time. Those that loaded positively onto this factor tended to disagree or strongly disagree with the following statements: “My schedule makes it hard or impossible for me to use public transportation,” (indicating that there schedule does NOT make it hard for them to use public transit) “I am too busy to do many things I’d like to do,” (indicating that they are NOT too busy to do the activities that they would like to do) and “Most of the time, I have no reasonable alternative to driving” (indicating that they DO have reasonable alternatives to driving). These respondents may have no alternative to driving.

Results

Since our dependent variable, primary vehicle type, consists of six mutually exclusive categories, we developed a multinomial logit model for vehicle type choice. As mentioned in the previous section, these six categories are: Small/Compact, Midsize car, Large car, SUV, Luxury, and Luxury SUV.

The final model has five alternative specific constants and 22 alternative specific variables that represent nine different variables. The table below presents the estimated coefficients (with the respective p-values in parentheses). The rho-squared value of the final model is 0.252, which is quite good for a model of this type. In comparison, the rho-squared for the market share model is 0.116, which indicates that the model with only the constants explains about 12% of the information in the data, and that our full model is able to contribute significantly to explaining the choice of vehicle type, despite the obvious difficulties associated with the heterogeneity in the choices of vehicle type, and impacts of eventual unobserved variables that might affect the choice of the vehicle one owns.

In particular, as pointed out in previous papers in the literature, the choice of the vehicle to buy is usually a choice that is made at the household, and not individual, level. Additionally, the choice of the vehicle to buy is affected by the other vehicle(s) that the household eventually owns (or plans to purchase in the near future). Thus, the choice of the various vehicles that are owned by a household (for households that own more than one vehicle) is a joint choice, and should be model as such. Unfortunately, in this dataset we only have information on the number of vehicles owned/leased by a household (and, therefore, we know of the eventual presence of other vehicles, in addition to the "primary" vehicle), but we do not have information about the type of vehicles that are owned, apart from the primary vehicle. This somehow limits the ability of the model to predict the choices of a household that might decide, for example, to own a SUV and a compact car to fulfill their mobility needs.[12] Despite this limitation, the estimated model provides some useful information on the relationship between various groups of variable and the type of primary vehicle that an individual owns.

[12] In our dataset, the information about such a HH would be included as "owning an SUV as the primary vehicle that is used most often and another unknown vehicle", or as "owning a compact car as the primary vehicle that is used most often and another unknown vehicle".

Table 11. Estimated Coefficient of Vehicle Type Choice Model

	Dependent Variable: Vehicle Type					
	Small/ Compact	*Midsize*	*Large Cars*	*SUV*	*Luxury*	*Luxury SUV*
Age	0.059 (0.013)	(base)	0.252 (0.000)	0.222 (0.000)		1.176 (0.000)
Age^2	-0.001 (0.045)	(base)	-0.003 (0.001)	-0.002 (0.000)		-0.014 (0.000)
Female		(base)				0.603 (0.000)
Number of children under 18 years old in the household	-0.266 (0.048)	(base)		0.488 (0.000)	-0.521 (0.014)	
FS Car as a tool	0.355 (0.005)	(base)				
FS Time/Mode constraint (reversed)	-0.35 (0.007)	(base)				-0.584 (0.047)
FS Established in life	-0.242 (0.067)	(base)			0.5 (0.025)	
Household income	0.109 (0.084)	(base)			0.22 (0.014)	0.479 (0.001)
Interaction HH Income with urban neighborhood type		(base)			0.121 (0.026)	-0.16 (0.078)
Constant	-0.911 (0.000)	(base)	-6.181 (0.000)	-5.646 (0.000)	-2.561 (0.000)	-29.696 (0.000)
Number of observations	529					
Log-likelihood at 0	-947.84					
Log-likelihood at market share	-801.05					
Log-likelihood at convergence	-708.53					
ρ_{EL}^2 $(adjusted\ \rho_{EL}^2)$	0.252 (0.200)					
ρ_{MS}^2 $(adjusted\ \rho_{MS}^2)$	0.116 (0.088)					

Note: p-values are reported in parentheses below the estimated coefficients

The socio-demographic characteristics used in the model provide interesting insight into vehicle type choice: we used age and age squared to allow for a non-linear relationship of this variable with the choice of certain vehicle types. As shown in the model, the probability that an individual owns a large car, SUV, or Luxury SUV increases with age. Similarly, those who are older are more likely to associated higher utility with and own a small/compact vehicle (probably, as an effect of the HH vehicle fleet composition, as discussed above), even if to a lesser degree.

Those with children living at home are more likely to own SUVs (and/or vans, which were also included in this category) and less likely to own small/compact and luxury vehicles: parents need the utility of an SUV which is not offered by smaller vehicles. Parents are more likely to associate value with the seating space, storage capacity, and general comfort typically associated with these vehicles. Also looking at household income, our model shows that higher household income has a positive impact on the likelihood to own a small/compact vehicle, a luxury vehicle, and a luxury SUV. While the impact of household income on luxury brand vehicles (either cars or SUVs) is pretty straightforward, the impact of household income on the likelihood to own a small/compact car is likely associated with the joint choice of the multiple vehicles owned by more affluent households described above. For instance, in a high income 2 car – 2 person household, the survey respondent may have equal access to both vehicles; however, one vehicle is mainly used by the spouse, leaving the respondent with the other vehicle whose information is reported in the survey. Women were found to be more likely to own luxury SUVs. This reaffirms findings from a recent Edmonds.com study which found that women now account for 41% of new luxury vehicle purchases (http://www.detroitnews.com/story/business/autos/2016/09/06/women-buying-luxury-vehicles/89936258/).

The inclusion of factors extracted from the attitudinal variables provide important insights into further understanding vehicle type choice behavior. As described in the methodology section, we included three factors as explanatory variables in the model. The inclusion of the "Established in life" factor was an attempt to capture the effect of stage of like (in particular, a relevant variable to capture younger millennials' behaviors and lifestyles). In this instance, those who have higher values for this factor are more likely to own luxury vehicles and less likely to own small or compact vehicles. This result is not surprising, considering that luxury vehicles are expensive and individuals who are more certain about life (and perceive that they are less in a transient and unstable stage of their life) have are more likely to be able to purchase more expensive vehicles.

Those who recognize higher "utilitarian" value to the use of a car (i.e. have higher "car as a tool" factor scores) are more likely to own small or compact vehicles. Small/compact vehicles, in most cases, do not fill a niche market and they are simply seen as a way to get from origin to destination while minimizing purchase and maintenance cost; they are not as comfortable as luxury vehicles and they do not provide the space of an SUV.

Land Use Characteristics

The interaction term of household income and urban neighborhood type was included in the model as a way to account for the different behavior of urban households regarding the choice of the vehicle to own.[13] In addition to the base effect of household income on the vehicle type choice that was discussed earlier, we find that, not surprisingly, individuals with high household incomes that live in urban neighborhoods are more likely to own luxury vehicles and less likely to own luxury SUVs. These effects are introduced in the model as corrections to the base effect

[13] In addition to the impact on the type of vehicle that is owned, land use characteristics are expected to affect the number of vehicles that are owned by a household. We plan to explore this relationship in future steps of the research, through the estimation of a car ownership model that accounts for the impact of individual and land use characteristics on the number of vehicles owned by a household.

of the household income on vehicle choice, meaning that higher income households that live in urban areas are not as likely to own a luxury SUV as the higher income households that live in other neighborhood types (though they are still more likely to choose these vehicles than lower income households), and they are even more likely to own a luxury car (and not an SUV) than the high income households that live in other neighborhoods. More details can be found in Berliner and Circella (2017).

Propensity to Modify Vehicle Ownership

In the California Millennial Dataset, we also collected information about the respondents' self-reported willingness to buy/lease a vehicle (Figure 27) and their propensity to sell/get rid of their currently own vehicle within the next three years (Figure 28). As shown in Figure 27, millennials in general, and older millennials in particular, more often report that they are more inclined to purchase/lease a car within the next three years, compared with other age groups. This is consistent with expectations, because millennials, particularly millennials who lives in urban neighborhood, have lower car availability compared to their older counterpart, who has already acquired a vehicle or has higher accessibility to a car otherwise owned in the household.

This trend also confirms that very often millennials are in a transient life stage, and their zero- or low-car ownership might be only a temporary factor, subject to change during their near future. The finding may have, in particular, consequences on the car ownership status of urban millennials. This group of young adults are often found to live in dense neighborhood and not to own a car. High expectations have been posed on this group in eventually continuing to transform the future of transportation, and eventually help in the transition towards more sustainable mobility. However, the high propensity to purchase a car during the next three years of the respondents included in this group represent a potential threat to some sustainability goals, and signals that probably most part of the low car ownership status of this group is not likely to last as these individuals age and transition in the following stages of their life.

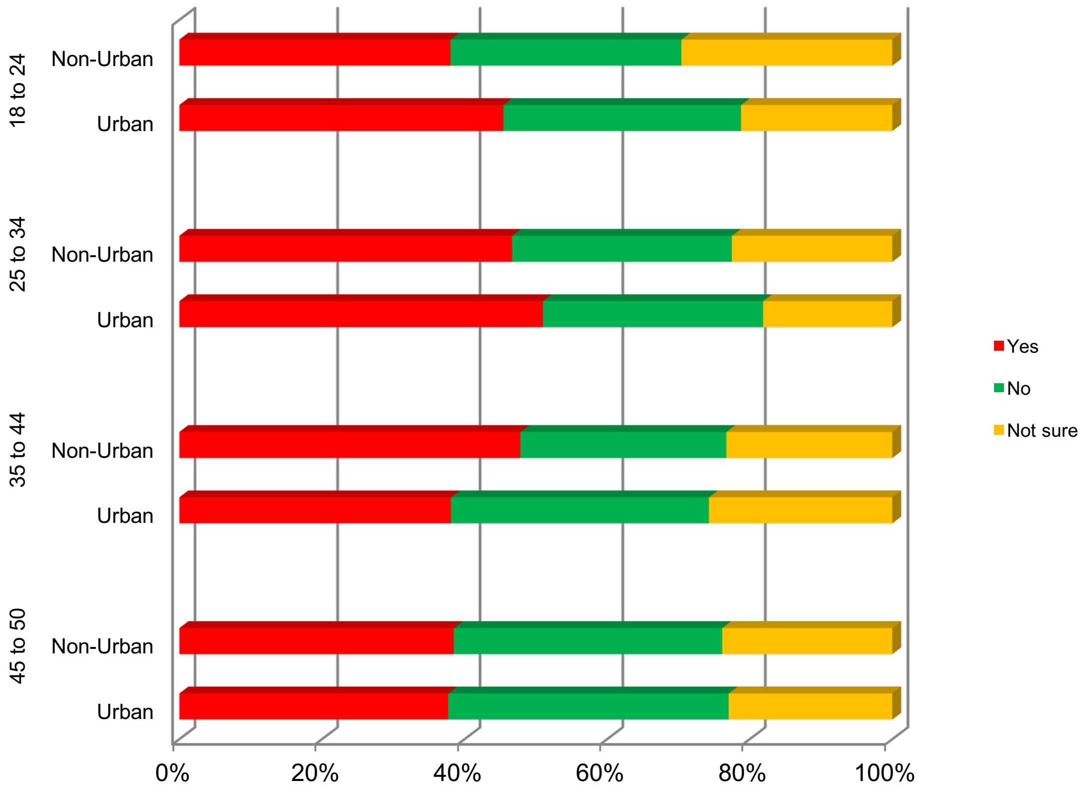

Figure 27. Distribution of individual's willingness to purchase/lease a vehicle within the next three years by age group and neighborhood type

Figure 28 presents individual's propensity to sell/replace of their currently owned vehicle within the next three years. As indicated in the graph, car ownership decreases from rural to suburban and urban neighborhoods among both millennials and Gen Xers. Interestingly, the propensity to sell a car is higher among millennials who own a car and lives in urban neighborhood compared to both their older peers who live in the same areas, and to millennials who live in other neighborhood types. In contrast, the willingness to replace their current vehicles is higher among the members of Generation X, in particular among those who live in rural neighborhood.

We plan to further investigate the topics that are summarized in these figures, through the development of models of the propensity to change the level of vehicle ownership in the household, and investigate the factors affecting these trends. This topic and the type of vehicle that the respondents would consider buying, as also reported in the survey are of potential interest to auto makers and planning agencies. They will likely affect future demand for car sales and use. Further, in future stages of the research, we plan to investigate the relationships between the adoption of shared mobility services and the propensity of respondents to modify their level of vehicle ownership.[14]

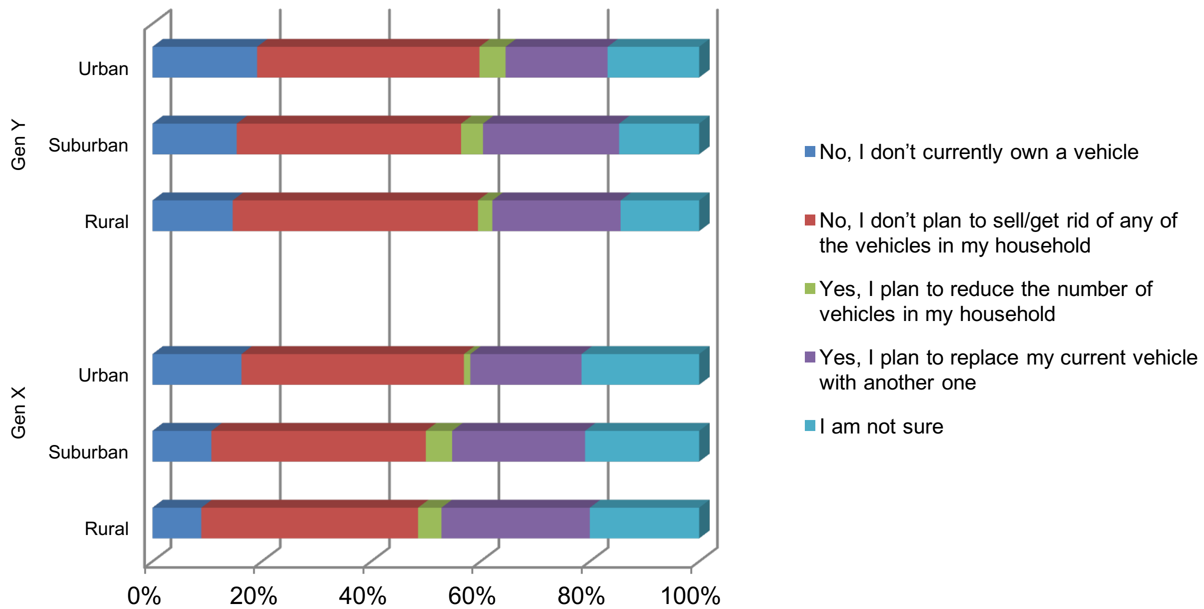

Figure 28. Distribution of individuals' propensity to sell/get rid of their vehicle within the next three years by age group and neighborhood type

[14] This will provide additional information on the likely changes in car ownership and use, as the adoption of shared mobility services become more popular in future years.

Conclusions and Next Steps of the Research

Millennials include a very large segment of the population, who often are early adopters of new trends and technologies that later are adopted by other segments of society. Thus, improving the understanding of the factors and circumstances behind millennials' mobility choices is of outmost importance for scientific research as well as for planning processes. Previous studies have highlighted how millennials often have different tastes, lifestyles, consumer and travel behavior from those of previous generations at the same stage in life. Still, today's young adults are in a "transitional" stage of life, in which they are building the basis for their future life, family and work career. Thus, their current choices are expected to be a sum of lifecycle, period and generational effects: their current behaviors are not necessarily going to last as millennials become older, and transition to more stable life stages.

This study investigates millennials' choices, through the analysis of a comprehensive dataset that includes information on many of the variables that have been attributed a role in affecting new travel trends and adoption of emerging transportation services. These variables were difficult to control in previous studies, which were often limited by the lack of availability of information on specific variables (such as studies based on the analysis of NHTS data), or the use of non-representative samples (as in the case of convenience samples, e.g. collected among university students).

The study builds on an extensive research effort carried out with the collection of the California Millennials Dataset, an unprecedented dataset collected in 2015, which includes information on individual preferences, lifestyles, adoption of technology, car ownership and travel behavior for approximately 2400 residents of California, including both millennials (young adults, 18-34, in 2015) and members of preceding Generation X (middle-age adults, 35-50). The study allows the investigation of several components of the emerging trends in travel demand and adoption of transportation technology in California.

In this stage of the study, we matched the information contained in the California Millennials Dataset with additional variables of interest including land use and built environment data available from other sources, based on the geocoded residential location of the respondents. The data provide a wide variety of land use and accessibility measures available through the US EPA Smart Location Dataset and the walk score, bike score and transit score obtained from the commercial website Walkscore.com. Using the geocoded information on the residential location, and the information provided by the respondents in the survey, we carefully cleaned and recoded the data, to improve the quality of the responses and identify internal and external inconsistencies and potential outliers that may lead to noise in the data. Further, we developed a set of weights, through the application of both cell weights and the iterative proportional fitting (IPF) raking approach, to correct the distribution of cases in the sample, and reduce the non-representativeness of the data based on the region of California where the respondents live, neighborhood type, age, gender, student and employment status, household income, race and ethnicity and presence of children in the household.

We developed a number of analyses to investigate the complex relationships behind residential location and mobility choices of California millennials and members of Generation X. First, through the use of data reduction techniques, we applied a factor analysis approach to the 66 variables that collected information on the respondents' attitudes and preferences towards a number of dimensions, including travel mode preferences, adoption of technology, environmental concerns, land use preferences, etc. We extracted a set of 17 factors that measures the main attitudinal constructs on a number of topics, and can be used in the analysis of choices related to travel behavior, residential location, and car ownership and use.

We analyzed the attitudinal profiles and individual characteristics for many subgroups of individuals: not surprisingly, millennials that live in urban, suburban or rural areas often manifest rather different attitudinal patterns from their counterparts in older age groups. We also analyzed the adoption and frequency of use of smartphone apps among different sociodemographic groups: urban millennials are heavy adopters of these services, and on average show higher adoption of these technologies for various purposes, including accessing information about the means (or combination of means) of transportation to use for a trip, finding information about trip destinations or navigating in real-time during a trip. Large differences are also observed in the adoption of shared mobility services among urban and non-urban populations: not surprisingly, millennials tend to adopt these new technological transportation services more often than the members of Gen X, in particular in urban areas.

We further analyzed the relationship between accessibility and adoption of multiple modes of transportation (multimodality, and/or intermodality) among the members of various sub-segments of the population. For this analysis, we further classified millennials in two groups, depending on their living arrangements and household composition, identifying the *independent millennials* (who do not live anymore with their parents, and have already established their own household), and the *dependent millennials* (who live with their parents), as a better way to control for the residential location of the respondents (as the residential location for dependent millennials has likely been chosen by their parents, and not by the millennials themselves). We compared the level of accessibility of the place of residence and the adoption of multimodal travel of the two groups of millennials with those of the older members of the Generation X.

Independent millennials were found, on average, to have the highest values for all accessibility measures. Further, important differences are observed among dependent and independent millennials: dependent millennials tend to live in areas that have the lowest levels of accessibility by non-car modes, probably due to the residential location chosen by other members of the households (e.g. young adults who live with their parents). This sharply contrasts the residential location of independent millennials who are more often found to live in locations with higher accessibility. Central locations are more conducive to the adoption of greener and non-auto commute modes (and/or may reinforce the propensity of young adults to use such modes or to adopt multimodal travel). At the other end of the spectrum, Gen Xers rely heavily on the use of cars for their commute. Interestingly, at least a part of dependent millennials are found to drive less than their older peers in spite of living in neighborhoods that are less conducive to multimodality and to the use of non-auto modes. The findings suggest that a higher component of the adoption of multimodal behaviors is associated with making these decisions by choice, rather than necessity.

In summary, and not surprisingly, accessibility and multimodality are positively correlated: residents of more accessible neighborhoods are more often found to be multimodal commuters. However, millennials, and especially dependent millennials, are found to make the most of their built environment potential, either due to individual choices, or the presence (or lack) of travel constraints. They are less likely to be mono-drivers and more likely to be multimodal commuters, even if they live in neighborhoods that are less supportive of such behaviors. This suggests that the connection between the built environment and travel patterns may differ by generation: in future steps of the research we plan to further investigate (and model) the relationships between accessibility and multimodal behavior among the members of the different generations, while controlling for other factors affecting residential and travel choices.

In order to investigate the impacts of various groups of variables on the mobility choices, and in particular on car use, of the members of the various generations, we estimated a log-linear model of the number of weekly vehicle miles traveled (VMT). We estimated both a pooled model for the entire sample, and a segmented model that allowed us to control for the effects of individual, household and land use characteristics on the VMT of millennials and Gen Xers, separately. All models have excellent goodness of fit: however, and very interestingly, among the three models that are presented, the model for millennials explains the lowest amount of variance in the data. This finding signals the higher heterogeneity and taste variation among the members of this group, and the increased difficulty in explaining their behaviors through the estimation of econometric and quantitative models. Traditional built environment variables such as population density and diversity of housing/jobs do not explain as much variation in VMT for millennials as for Generation X. Attitudinal variables and variables measuring the stage of life of the respondents (in particular, the living arrangements and the presence of children in the household) explain more variation for millennials than Generation X, confirming that millennials' travel choices are best explained by their attitudes and stage of life than by more traditional variables used in other studies.

We investigate the relationship of individuals belonging to the various age groups with car ownership and the type of vehicle that is owned in the household. Not surprisingly, independent millennials that live in urban areas are found to own fewer cars per driver in the household. This finding, which matches the reduced needs for a car in denser (and more accessible) central areas, and the stereotype of millennials that more often prefer to own fewer vehicles and adopt other modes of transportation more often, might be short-lived though. Many older millennials who live in urban areas actually report that they do plan to purchase a new vehicle in the near future, thus confirming that their zero- or low-vehicle ownership status is probably the result of the individuals' transient stage of life, rather than the long-term effect of strong preferences towards vehicle ownership and use. During future stages of the research, we plan to study how car ownership varies across different groups of the population through the estimation of car ownership models that investigate how various sociodemographic characteristics, individual preferences, and land use features affect household car ownership, and the use of latent class analysis (and latent class modeling) to further identify the impact of taste heterogeneity among different groups of individuals with regard with vehicle ownership and travel behavior.

In order to investigate the preference towards the purchase of various vehicle types among different groups of users, in this stage of the research we estimated a multinomial logit model (MNL) of vehicle type choice, using socio-demographic characteristics, residential location and land use characteristics, and personal attitudes and preferences as explanatory variables. We focused on individuals that bought or leased a used or new vehicle that is model year 2010 or newer for this analysis, in order to avoid the noise associated with the eventual presence of vehicles that were gifted to the individual by other family members, or vehicles that were purchased out of contingencies (e.g. as in the case of older vehicles, for which only few available options might be available in a limited price range).

During the next stages of the research, we plan to capitalize on this ambitious research program for the investigation of the mobility of millennials in California. In particular, we plan to further investigate the heterogeneity in the population of millennials (and older adults) through the development of cluster or latent class analysis to analyze different profiles of people, and investigate the proportion of millennials and Gen Xers that live in urban areas, have dynamic lifestyles, are heavy users of social media, own zero (or few) cars, use public transportation, and adopt new technologies, and what differences exist with the other segments of the millennial population. Further, we plan to investigate (and model) the relationships between accessibility and multimodal behavior among the members of the different generations, while controlling for other factors affecting residential and travel choices, including household size and composition, individual attitudes and lifestyles, and adoption of technology. We also plan to investigate the relationships behind the adoption of shared mobility services and other components of travel behavior, among various sub-segments of the population.

In particular, we plan to evaluate the relationships and latent constructs behind the adoption of shared mobility services, such as carsharing or on-demand ride services such as Uber or Lyft, and analyze the impact of various factors affecting the use of these services in various geographic regions and neighborhood types, and among different segments of the population, through the estimation of multivariate models of the adoption and frequency of use of each type of shared mobility services. We will investigate the impact of residential location and neighborhood characteristics on these choices, and estimate bivariate models to explore the relationships between the adoption of shared mobility services and:

a) The use of other travel modes, including driving alone and using public transportation;
b) Auto ownership; and

c) The individual's reported willingness to change the level of auto ownership, e.g. reducing the number of vehicles in the household, buying a new vehicle, etc.

Further, the study will explore heterogeneity in travelers' behavior, with respect to the adoption of shared mobility services, travel behavior, individual lifestyles and tastes, as a way to investigate differences in the observed relationships among various groups of individuals. The study will provide important insights into the impact of the adoption of new shared mobility services on other components of travel demand, VMT and auto ownership in various regions of California and land use types, controlling for individual characteristics and differences among segments of the population.

Finally, the data collection effort for this study was designed as the first step of a longitudinal study of the emerging transportation trends in California, designed with a *rotating panel* structure, with additional waves of data collection planned in future years. In future stages of this research, we plan to expand the data collection also through other channels, eventually also through the creation of a paper version of the survey, in order to expand the target population for the study, and reach specific segments of the population, e.g. elderly or people that are not familiar with the use of technology or who do not have easy access to the internet and would not likely complete an online survey. Also, we are considering creating a version of the survey in Spanish, in order to better reach the California population of Latinos and increase the response rate among the Hispanic minority. The analysis of the information collected through multiple waves of survey will provide valuable information on the likely changes happening in travel demand, and will provide insights into the impacts of the adoption of a number of new transportation services on future transportation in the state.

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List of Acronyms Used in the Document

ACOP	American Consumer Opinion Panel
Caltrans	California Department of Transportation
CEC	California Energy Commission
EPA	(United States) Environmental Protection Agency
FHWA	Federal Highway Administration
Gen X	Generation X (Middle-aged adults, 35-50 y.o. in 2015)
Gen Y	Generation Y (Young adults, 18-34 y.o. in 2015)
GHG	Greenhouse Gas
HH	Household
ICT	Information and Communication Technology
IPF	Iterative Proportional Fitting
IT	Information Technology
IRB	Institutional Review Board
ITS	Institute of Transportation Studies
LDT	Light Duty Trucks
LTE	Long Term Evolution (a 4G mobile communications standard)
LU	Land Use
MNL	Multinomial Logit (Model)
MPO	Metropolitan Planning Organizations
MTC	Metropolitan Planning Organization (San Francisco Bay Area)
NCST	National Center for Sustainable Transportation
NHTS	National Household Travel Survey
SACOG	Sacramento Area Council of Governments
SANDAG	San Diego Association of Governments
SCAG	Southern California Council of Governments
STEPS	Sustainable Transportation Energy Pathways
SUV	Sport Utility Vehicle
TDM	Transportation Demand Management
TNC	Transportation Network Company
TRB	Transportation Research Board
UC	University of California
UC Davis	University of California, Davis
UCLA	University of California, Los Angeles
US DOT	United States Department of Transportation
VMT	Vehicle Miles Traveled