# The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior

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National Center for Sustainable Transportation

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## Acknowledgments

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## EXECUTIVE SUMMARY

Emerging technologies and shared mobility services are quickly changing transportation. The popularity of these services is particularly high among millennials and those living in the dense central parts of cities. Still, the reasons behind the adoption of these services and their impacts on the use of other transportation modes and on total travel demand are largely unclear.

How are shared mobility services changing transportation demand and supply? This report provides useful insights to answer this question. The research explores the use of various types of shared mobility services in California, focusing in particular on the factors affecting the adoption and frequency of use of ridehailing services (such as those provided by Uber and Lyft), and the impacts that the use of these services has on other components of travel behavior. We analyze a dataset that we collected with a detailed online survey in fall 2015 as the first round of data collection in a panel study of emerging transportation trends and adoption of technology in California. More than 2,000 respondents, including millennials (i.e., young adults born between 1981 and 1997) and members of Generation X (i.e., middle-aged adults born between 1965 and 1980), completed the survey.

### Research questions

- How are shared mobility services (including carsharing, ridehailing and bikesharing) used in California?
- What factors drive the use of ridehailing? Under what circumstances individuals are more likely to use Uber and Lyft?
- How frequently do Californians use ridehailing, and how does that frequency vary with sociodemographics, built environment characteristics, individual lifestyles and attitudes?
- What limits/encourages the use of these services?
- What are the impacts of ridehailing services on other components of travel behavior, such as the amount of individual driving, the use of public transit and walking/bicycling?

### Use of shared mobility in California

We present descriptive statistics on the awareness, familiarity and use of various shared mobility services including ridehailing, carsharing, and bikesharing in California. The results show that the percentage of respondents that are familiar with and use shared mobility services is higher among urban dwellers and residents of the large metropolitan areas in the State. Even if ridehailing is a newer type of service (which was more recently introduced to the market), the users of Uber and Lyft significantly outnumber the users of other emerging

transportation services. Residents from the San Francisco Bay Area are more likely to be active users of all emerging transportation services in their hometown/city.

## Adoption of Uber/Lyft

To investigate the factors that affect the adoption of ridehailing, we estimate several models that help assess the role of individual characteristics and residential location in affecting these choices. The results of a binary logit adoption model of Uber and Lyft show that:

- Higher-educated older millennials (between 25 and 34, in 2015) are more likely to use ridehailing than other groups.
- Greater land-use mix and more central urban locations are associated with higher adoption of Uber and Lyft.
- Higher adoption is observed among individuals who make a large number of long-distance trips, and in particular those who travel more frequently by plane.
- The degree of familiarity with ICT and other technology-enabled transportation services positively affects the adoption of Uber/Lyft.
- Those who have previously used taxi and carsharing more likely use ridehailing.
- The rate of adoption is significantly higher among individuals with stronger *technology-embracing*, *pro-environment*, and *variety-seeking* attitudes.

To better account for individuals' heterogeneity and taste variation with respect to the use of Uber/Lyft, we estimate a latent-class adoption model:

- Users of ridehailing can be grouped into three well-defined latent classes, based on their individual and household characteristics, lifestyles and stage in life.
- The highest adoption rate (47%) is observed among the members of the class that is largely composed of higher-educated independent millennials who live in more urban locations. The adoption rate in this class is higher for individuals that make more long-distance leisure trips and are more frequent users of ICT and smartphone apps.
- The second highest adoption rate (27%) is observed among the members of a class mainly composed of affluent older Gen Xers and dependent millennials living with their families. The adoption of ridehailing in this class is higher for individuals who make more long-distance trips for business purposes, have higher income and use ICT more often.
- The lowest adoption rate (5%) belongs to the members of the class with the highest share of rural dwellers and of individuals with low education and/or who live in low-income households. Land-use mix and transit accessibility play an important role in affecting the use of ridehailing among the members of this class.

## Frequency of use of ridehailing

We estimate an ordered probit model with sample selection and a zero-inflated probit ordered model to explore the impacts of various explanatory variables on the frequency of use of Uber/Lyft:

- About 17% and 15% of millennials used ridehailing less than once a month and at least once a month, respectively, while these shares decrease to 14% and 8%, respectively, for the member of Generation X.
- Sociodemographics are good predictors of adoption but not so much of frequency.
- Individuals who live in a zero-vehicle household are more likely to use Uber/Lyft with higher frequency.
- Frequent long-distance travelers (by plane, in particular) use Uber/Lyft more often.
- Land-use mix and activity density (i.e., population and job density) impact the frequency of use of ridehailing.
- Individuals who frequently use smartphone apps to determine destination and route choice are more likely to both adopt ridehailing and use it more often.
- The frequency of use decreases for the individuals who report having strong preference to use (have) their own vehicle.
- There is competition among shared mobility services: carsharing users are more likely to also use ridehailing, but frequent users of carsharing tend to use Uber/Lyft less frequently.

## Limitations to the use of ridehailing

Participants were asked to evaluate what factors limit their use of ridehailing, and the importance of several service attributes in affecting their use of Uber/Lyft:

- The preference to use one's own vehicle was reported as the most important factor limiting the use of ridehailing.
- The concerns about comfort/safety and the cost of the service are respectively the second and third most reported factors limiting the use of Uber/Lyft.
- Users report that the short waiting time and the easiness to call a car are the most important reasons for using the service.
- More than 80% of respondents reported that parking (including both the difficulty of finding a parking space and the cost of parking) was a moderately important to extremely important reason affecting their decision to use Uber/Lyft.
- About 60% of the respondents reported that they have used ridehailing to avoid drinking and driving.

## Impacts of ridehailing on the use of other travel modes

We analyze the self-reported information on the effects that the last trip made by Uber and Lyft had on other travel modes:

- A large majority of the respondents (including both frequent and non-frequent users) reported that the use of Uber/Lyft reduced their use of a personal car.

- The use of ridehailing substitutes for some trips that would have otherwise been made by transit or active modes. This substitution effect is stronger among frequent ridehailing users, individuals that live in zero-/low-vehicle households and multimodal travelers.

- The majority of non-frequent users reports that they would have driven a car, gotten a ride from someone else, or taken a taxi if Uber/Lyft were not available.

- Somewhat concerning from the perspective of environmental sustainability and the promotion of active lifestyles, a larger proportion of millennials reduced their amount of walking and biking as the result of the use of ridehailing.

- Further, frequent users of ridehailing more often report that they are considering reducing the number of household vehicles than the rest of respondents in the sample.

Further, we employed a latent-class analysis approach to classify users based on the self-reported behavioral changes associated with the use of ridehailing. Three well-defined latent classes were identified:

- The largest class (53% of users in our sample, including most frequent users) is mainly composed of independent millennials who live in walkable neighborhoods that are highly accessible by transit and who are multimodal travelers. Ridehailing has mixed effects on these users, contributing to reducing the use of personal cars, transit and active modes.

- Ridehailing substitutes for the use of a personal vehicle among the member of the second largest class (37% of users) that is composed of affluent suburban dwellers with positive attitudes towards car ownership and use, and high VMT.

- The use of Uber/Lyft increases the use of public transit (e.g., providing access to transit stations) among a group of predominantly suburban dwellers who live in less accessible areas but try to be multimodal when possible and have pro-environmental attitudes. This group only includes 10% of users, who use ridehailing occasionally.

## Study limitations and next steps of the research

Several limitations affect this study and its ability to generalize the results to the population of residents of California. The characteristics of shared mobility services and of their users are continuously evolving, thus increasing the uncertainty about the observed relationships. Further, the cross-sectional nature of this dataset limits the ability to assess causality in the observed behaviors. During the next stages of the research, we plan to investigate the relationships between the use of shared mobility and the propensity to change household vehicle ownership. We will also broaden the investigation to include pooled ridehailing services (such as UberPOOL and Lyft Line). The availability of longitudinal data will allow us to monitor the adoption of shared mobility in California and the related changes in travel behavior, and will help disentangle causality in the complex relationships among the adoption of these services, other components of travel behavior and eventual changes in household vehicle ownership.

## Introduction

Transportation is changing quickly. Information and communication technologies, combined with increased availability of locational data and smartphone apps, provide unique opportunities for the introduction and massive deployment of new transportation services. Among these technology-enabled options, modern shared-mobility services merge the advantages of mobile communications and instant reservations with the principles of the sharing economy. In doing so, they separate access to transportation services from the fixed costs of auto ownership (and fixed schedules of public transportation). These technology-enabled services can affect travel behavior in multiple ways, e.g. through increasing the number of available options for a trip, reducing travel uncertainty, and providing easier access to a vehicle (or a car ride) also to those individuals that live in households that do not own a car.

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

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

One of the most controversial and rapidly growing forms of shared-mobility services includes *on-demand ride services* (also known as *ridehailing*, *ridesourcing*, or *transportation network companies*, or *TNCs*), such as Uber and Lyft in the U.S. market. On-demand ride services are similar to taxi services in that they connect travelers requesting a ride with the pool of available

drivers through a smartphone application. They are different from dynamic ridesharing apps/services, such as Carma in the U.S. or BlaBlaCar in Europe, because drivers who participate in dynamic ridesharing programs only offer rides to other travelers (with similar destinations) along the route of a trip the driver would be taking anyway. Instead, drivers of on-demand ride services usually "chauffeur" passengers to their destination independently from the drivers' mobility needs.

Even though ridehailing services are becoming more common in many developed and developing countries, information about the adoption rate, the factors affecting their use and the potential effects of these services on the use of other modes is still limited. Among their potential effects, ridehailing services can (a) provide flexible alternatives to driving; (b) offer first- and last-mile access to public transportation, increasing public transportation efficiency and convenience; and (c) provide a ride home outside the hours of operation of public transit, or at a time in which traveling by transit and/or accessing/egressing transit stops may be considered unsafe (Hallock and Inglis 2015, Shaheen et al. 2015a, Taylor et al. 2015, Circella et al. 2016). On the other hand, shared-mobility services may also generate additional trips, inducing additional demand for travel (as a result of the increased transportation accessibility and reduced travel costs) and might reduce public transit ridership in particular in places where the quality of public transit services is lower. Rayle et al. (2014) suggested that TNCs may be a substitute for single occupant driving trips. Early adopters of various types of shared-mobility services, including carsharing, bikesharing and on-demand ride services, tend to be more highly-educated young adults who live in urban areas (Buck et al. 2013, Rayle et al. 2014, Taylor et al. 2015, Circella et al. 2016, 2017a). This may be due to the familiarity of the younger generation with technological solutions, or because of residential locations that are more conducive to the adoption of these services and the local availability of new mobility options. This finding seems to match other characteristics of young adults, who tend to live in more central locations, own fewer cars, drive less if they own one and use alternative modes of transportation more often (Kuhnimhof et al. 2012, Polzin et al. 2014, Brown et al. 2016).

The goal of this study is to investigate the factors affecting the use of shared mobility – in particular ridehailing services – and the different rationales behind the adoption patterns of different groups of users, the circumstances under which travelers use these services more often, the limitations to the use of these services and the impacts that the use of these services has on other components of travel behavior. We analyze data from the California Millennials Dataset, a rich dataset that was collected in fall 2015 as the first round of data collection in a panel study investigating emerging travel patterns and adoption of technology in California among selected segments of the population. In this first round of data collection, a comprehensive online survey was designed and administered to a sample of more than 2000 residents of California, including both members of the millennial generation (18 to 34 years old in 2015) and the previous Generation X (middle-age adults, 35 to 50 years old in 2015). The survey collected a wealth of information that focused, among other topics, on the awareness, adoption, and frequency of use of modern technologies and new shared-mobility services, and many factors that are potentially behind their use.

## Literature Review

In the following subsections we will focus on studies that have focused on the following types of shared mobility services: ridehailing, carsharing, and bikesharing. These studies typically fall into two categories: those that investigate the factors behind the adoption of these services, and those that focus on the impact of these services on other transportation modes and the transportation network.

### Ridehailing

One of the most controversial and rapidly growing forms of new shared mobility services includes ridehailing (or on-demand ride services) such as Uber and Lyft. On-demand ride services primarily resemble taxi services. Uber, one of the key providers of this type of services, started the UberBlack platform in March 2009, followed by the launch of UberX, i.e., a service that directly competes with local taxi services, in July 2012. Moreover, in March 2015, UberPOOL was launched in San Francisco, serving as a carpooling application by providing opportunity to decrease an individual's fare through allowing the concurrent use of the services with other users (Mcbride 2015). After their initial launch, the availability of these services was later extended to other major metropolitan areas across the country. As of June 2015, Uber offered more than 1 million daily rides across the world, about 10 percent of which in China[1]. Shaheen et al. (2015) report that Uber and Lyft currently operate in more 300 and 60 U.S. cities, respectively.

Little is known about the overall impacts of on-demand services on passenger travel, largely due to lack of information about the scale and performance of on-demand ride services. Many of the existing sources include narrative and non-scientific studies. For example, Licea et al. (2015) report that the number of Uber vehicles in New York overtook the number of yellow taxicabs in March 2015[2]. Yellow Cabs made on average about 126,000 fewer daily trips in November 2016 compared to its average in the same month in 2010, before on-demand ride services became popular in New York City – a drop of 27% (from about 463,000 to about 337,000) (Hu 2017). In addition, many business travelers seem to replace the use of taxi by Uber and Lyft: according to Certify, a travel expense management company, use of on-demand ride services has surpassed the use of taxicabs among business travelers in the second quarter of 2015, the main reason for which is believed to be the relatively lower fare of these services[3].

The rapid expansion of the market for on-demand ride services has generated a strong debate, particularly, over its disrupting effects on the taxicab industry, which operates under more constrained regulatory conditions. Taylor et al. (2015) recommend that policy makers address these critical challenges through obtaining a consistent policy among both TNCs and traditional

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[1] Available at http://time.com/3914378/uber-china/ (Last accessed on March 14, 2018).

[2] Available at http://nypost.com/2015/03/17/more-uber-cars-than-yellow-taxis-on-the-road-in-nyc/ (Last accessed on March 14, 2018).

[3] Available at http://www.certify.com/CertifySpendSmartReport.aspx (Last accessed on March 14, 2018).

taxi companies, while promoting innovation to achieve more sustainable and safe transportation. However, policy makers would not be able to develop such efficient guidelines without understanding the potential effect of the adoption of on-demand ride services, including the potential relationships with long- to short-term decisions including residential and business location, travel patterns, and mode choice.

According to an online national tracking poll from June 2015[4], respondents who live in urban areas reported that they used on-demand ride service Apps more frequently than users in suburban and rural areas. Another study showed that frequent users of on-demand ride services in San Francisco mainly comprised of higher educated young adults, who own fewer vehicles and travel more frequent with companions (Rayle et al. 2014) . However, as these services become increasingly common in many parts of the country, future adoption rates and the overall impact of the adoption of these services on the use of other modes will depend on many factors. These factors include the perceived convenience of using these services, based on individuals' residential location and availability of other travel alternatives, and on whether current users will continue to use these services with the same frequency as they transition in their stages of life and move to other residential locations.

It is currently difficult to ascertain how riders change their behaviors with regard to the use of other transportation modes as a result of the adoption of ridehailing (Taylor et al. 2015). On-demand ride services may substitute for single occupant driving trips: for example, 40% of users in San Francisco reported that they have reduced their driving due to the adoption of on-demand ride services (Rayle et al. 2014). This study also discussed how on-demand ride services could be used in place or in connection with public transit. In a previous report from this research project, the research team discussed how a larger proportion of millennials reported that the overall effect of their last trip with an on-demand ride service company such as Uber or Lyft was to substitute for a trip they would have done by walking or biking, whereas a larger proportion of members of the previous Generation X reported that their Uber/Lyft trip replaced a trip that they would have otherwise made by car (Circella et al. 2016). A survey of 4,500 users of shared-mobility services revealed that frequent users of shared mobility tend to use public transit more often and are more multimodal. Some of this relationship may be due to the correlation of both behaviors with third-party variables such as low car ownership or living in more accessible locations. However, the majority of the trips made by on-demand ride services occurred between 10 pm and 4 am, when public transit either runs very infrequently or does not run at all (Shared-Use Mobility Center 2016), suggesting that at least to a considerable extent there is a true complementarity effect at work. On the other hand, a substitution counterexample could be that, according to statistics from the San Francisco Bay Area Rapid Transit (BART), ridership to and from the San Francisco and Oakland airports dropped by 6.5 and 4.5 percent respectively (at a time of continuous increases in the total number of passengers flying to/from these airports) while Uber and Lyft ridership to the same locations

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[4] Available at http://morningconsult.com/wp-content/uploads/2015/06/150505_crosstabs_mc_v2_AD.pdf (Last accessed on March 14, 2018).

soared substantially compared to 2014 after these services were allowed to provide rides to/from these airports (Cabanatuan 2017). A recent report from UC Davis researchers Clewlow and Mishra (2017) presented the results of descriptive statistics based on data collected in seven major US cities between 2014 and 2016. The authors found that the use of Uber/Lyft often contributes to a reduction in transit ridership, quantified in approximately 6% and 3% reduction in trips that would have otherwise been made by public bus or light rail, respectively. However, the study did not further investigate differences in the impacts of ridehailing among different groups of users, and/or in various geographic contexts (and therefore in presence of different levels of transit quality of service).

To date, there is no study that confirms the causal relationships among the use of on-demand ride services and different components of travel behavior, including multimodality, vehicle ownership and vehicle-miles traveled. Specifically, it is not yet clear the extent to which the adoption of shared-mobility services *causes* an increase (or a reduction) in transit use, as opposed to both of those conditions being caused by other variables (such as residential location, age/stage in lifecycle, and vehicle ownership) which in turns more broadly affect one's mobility style and travel behavior decisions. On-demand ride services may reduce the total amount of users' individual driving, but the pick-up and drop-off mileage may result in more total VMT (Cooper et al. 2010). Depending on the specific circumstances and characteristics of the local context, on-demand ride services may act as a VMT-additive or VMT-subtractive force. The overall impact on total VMT may depend on the typologies and distribution of drivers (Anderson 2014). Interviewing 20 drivers in San Francisco, Anderson (2014) classified drivers of on-demand ride services into three main groups, with the possibility of switching to each other's at any time: the first group of drivers is comprised of incidental drivers, who provide service occasionally. Incidental drivers look at the system as a ridesharing service, and are less inclined to take trips without shared destination, or to take trip that requires a long detour. According to Anderson (2014), the services provided by incidental drivers can be classified as VMT-subtractive services. The second and third groups are part-time and full-time drivers who count on the revenue from these services as a supplementary or the main source of their income. Full-timers provide rides over the entire course of day, or focus on rush hours[5], when the price is higher. In contrast to incidental drivers, both part-time and full-time drivers are willing to have longer detour and take trips without shared destination. Thus, the services provided by these two groups can be classified as VMT-additive services. Comparing the trips made by on-demand ride services and the matched taxi trips, Rayle et al. (2014) concluded that on-demand ride services could provide more efficient mobility with lower VMT, because on-demand ride services carried more passengers compare to paired trips with taxi.

Overall, it is reasonable to expect that new shared mobility services influence travel demand and mode choice, with the resulting effect varying based on the local context, the characteristics of the users, the built environment features and the transportation alternatives

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[5] Uber and Lyft defined a peak pricing priod, called *prime time* by Lyft and *surge pricing* by Uber, when demand outpaces supply. In this peak period, fares are higher.

that are available.[6] Newer services, such as those introduced with UberPOOL and Lyft Line, are also becoming popular: they allow multiple users to share a ride in the same vehicle (concurrent use of the services). If this type of service became dominant in the field of on-demand ride services, a likely reduction in overall VMT would result (Taylor et al. 2015).

In all the above studies, researchers applied various quantitative and qualitative research methodologies to explore the users' characteristics, potential markets, and to evaluate the impacts of emerging transportation services, each of which will always have specific advantages and disadvantages. As discussed by Shaheen et al. (2015), more research is needed to quantify the magnitude of changes in travel patterns and behaviors associated with the adoption of these emerging transportation services. Surveying travelers about how they used to travel before the introduction of these new transportation services and how they would have traveled in the absence of these services is a way to quantify the magnitude of these changes.

## Carsharing

Carsharing services are provided through a variety of business and operational models: carsharing programs are either fleet-based (e.g., Zipcar) or provided on a peer-to-peer basis (e.g., Turo, formerly known as RelayRides), where a user can rent a vehicle, when needed, from another user. While fleet-based carsharing services have already achieved popularity (predominantly in denser urban areas that generate enough demand for these services), peer-to-peer carsharing is emerging as an important alternative, due to its capability of expanding the benefits of carsharing to the suburbs and rural areas. In these areas, the lack of critical mass associated with the lower urban densities, the high proportion of home-based trips, and the higher auto-ownership rates, makes fleet-based carsharing unprofitable. Regardless of the ownership model that is adopted, carsharing programs are offered in two general operational models: (1) round-trip carsharing; and (2) one-way carsharing (with the latter that can be further classified as free-floating or station-based carsharing). As of January 2015, about 25 carsharing operators in the U.S. provide services to more than 1 million carsharing members (Shaheen and Cohen 2015).

Carsharing can potentially impact vehicle ownership and mode use, and can influence travel behavior in many ways. It allows individuals to access a vehicle when needed without bearing the associated fixed costs, e.g., cost of insurance, maintenance, and long-term parking. While this effect can contribute to increasing car use among those individuals that do not feel the need to (or cannot afford to) own a car (or travel far away from the place where their personal vehicle is located), it also contributes to reducing the importance of car ownership among the other users, i.e., those that already own one or more vehicles. Thus, carsharing may help to reduce vehicle ownership, allowing, at least, a portion of their users to get rid of one (or all) of their vehicles. Reduced vehicle ownership may create a positive feedback loop in which even

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[6] Available at http://ww2.kqed.org/news/2015/12/07/are-uber-and-lyft-really-disrupting-transportation (Last accessed on March 14, 2018).

larger VMT reductions are achieved if limit requirements for parking space are revised, which may allow construction of denser urban areas.

Round trip carsharing has been documented as a strategy to reduce car ownership and VMT in urban areas: it is suggested as an efficient tool to achieve the reductions in VMT and greenhouse gas emissions targeted in California State by 2040 (Caltrans 2015). The Caltrans document forecasts that a 5% increase in the adoption of carsharing can reduce statewide VMT by 1.1%. In another study, Cervero and Tsai (2004) found that 30% of the members of carsharing programs were willing to sell one or more of their vehicles, while other members postponed the purchase of an additional vehicle after using carsharing services for about two years. More recently, Mishra et al. (2015) found that vehicle holding among the members of urban carsharing programs is lower by about 10-14 percent, while the proportion of transit, biking and walking trips are all higher. However, early adopters of carsharing services tend to be higher-income individuals, who often report car disposal or postponement or complete avoidance of a car purchase to fulfill their mobility needs. The behavior of such early adopters may not be typical of later entrants to the carsharing market. In another study, Martin and Shaheen (2011) surveyed more than 6,000 members of carsharing programs in the United States and Canada, and concluded that adding another vehicle to the fleet of shared cars would replace 9 to 13 privately-owned vehicles among members of carsharing services, and would contribute to a 27-43 percent reduction in VMT as well as a 34-41 percent reduction in GHG.

One-way carsharing has been studied from several perspectives, including (1) optimum fleet size, the location of the stations, the size and number of vehicles; (2) strategies to deal with changes in demand for the service; (3) vehicle relocation systems (Shaheen et al. 2015b). Although numerous studies about one-way carsharing have been developed, the information available on the impact of this service on travel behavior is still limited. In a study of the Car2go service in Ulm (Germany), Firnkorn (2012)found that more than 25% of respondents would be willing to get rid of their personal vehicle. In a similar study among the subscribers to one-way carsharing in London, Le Vine et al. (2014) found that non-car-owning members reduced their frequency of grocery shopping as well as the time traveled for food shopping purposes. Kopp et al. (2015) confirmed this finding, noting that users of free-floating carsharing programs arrange their activities more cautiously. The authors also found that members of free-floating carsharing are more likely to be multimodal/intermodal: the share of biking is higher among the members of free-floating carsharing program, while the share of the car trip is significantly lower compared to the non-members.

Studies about how carsharing can affect the use of public transit are very limited: Chatterjee et al. (2013) suggested that carsharing can enhance the access to the other modes and, as a result, enrich multimodality, but they did not discuss how and to what degree this might happen. Still, other studies have suggested that, by eliminating the fixed costs associated with accessing a vehicle but increasing the marginal costs of traveling by car, carsharing might reduce total VMT. It may complement the use of public transit, increasing patronage for off-peak public transit services (Firnkorn and Müller 2011, Costain et al. 2012). Other studies showed that carsharing

can lead to opposite effects on the use of public transit, depending on the specific characteristics of each program. Le Vine et al. (2014) found that one-way carsharing is often used in place of public transportation, while round-trip carsharing is complementary to its use.

Schaefers (2013) qualitatively analyzed the cognitive process behind the use of carsharing program, based on in-depth interviewing of 14 users of carsharing services in the U.S., and classified the main motives affecting the use of carsharing into four main groups. According to Schaefers (2013), the underlying motivational factors behind the use of carsharing are cost, convenience, lifestyle, and pro-environmental/altruistic motives. In another study, Zheng et al. (2009) found that in addition to sociodemographic and the characteristics of the built environment, individual attitudes can strongly influence carsharing adoption rate. Celsor and Millard-ball (2007) found that the characteristics of the built environment are more important than individuals attributes in determining the potential market for carsharing.

Carsharing providers have also targeted universities and businesses, and are increasingly becoming part of several transportation demand management strategies. Clark et al. (2015) found that carsharing can change employer's habits of using a private car for commuting to work. Similarly, as of October 2014, 175,000 members of Zipcar in North America are identified as corporate members. In a survey of 523 corporate members in North America, Shaheen and Stocker (2015) found that 2 in 5 corporate members sold or postponed a vehicle purchase due to joining Zipcar, which is equivalent to the removal of 33,000 vehicles across North America.

## Bikesharing

Bikesharing programs are becoming an increasingly popular presence in many American cities. Bikesharing provides users with on-demand access to bicycles for short-distance trips that may appear too long for walking. Like carsharing, bikesharing is offered in various operational and business models. Bikesharing comes in a variety of forms, including dock-based bikesharing programs (by far the most common model of bikesharing services in large urban areas), dockless or GPS-based systems, and peer-to-peer bikesharing services. Bikesharing members can usually choose between daily/weekly passes and annual membership plans (Shaheen et al. 2014), with additional hourly rates that are charged based on pricing plans that discourage long bike rentals (in order to maximize the availability of shared bikes among members). As of 2015, bikesharing programs have launched in about 72 cities in the U.S., offering services by about 24,700 bikes in 2,440 stations (Shaheen 2015).

Bikesharing programs have been found to reduce driving and taxi use in almost every city in which they are available (Shaheen 2012). Shaheen et al. (2014) found that 50 percent of respondents reduced their automobile use due to bikesharing in a study of four different bikesharing programs in North America. Bikesharing has been associated with an increase in mobility and may increase transit use with coupling of bikesharing and transit stops (Nair et al., 2013).

While bikesharing in small cities tends to increase transit use by better serving the first and last mile access, in large cities bikesharing may reduce transit ridership through providing a faster and cheaper travel option for many trips (Shaheen 2012, Shaheen et al. 2014). Similarly, bikesharing programs may increase transit use for those living in the urban periphery, where access to public transportation by walk is limited, and decrease transit use for individuals in the urban core (Martin and Shaheen 2014). A similar pattern has been observed among the members of the Capital Bikeshare program in Washington D.C: 35% of casual users and 45% of annual members reported that their bikesharing trip substituted a public transit trip (Buck et al. 2013). Through analyzing users of the San Francisco Bay Area bikesharing program, Shaheen et al. (2015b) also observed significant differences between casual users and annual members in terms of trip purpose, trip duration, and home city. Noland et al. (2016) found differences in the times of use among casual bikesharing users and service subscriber in New York, NY. They found that bikesharing is used for transit access during rush hours, and that stations located along the same high-quality bicycle route see far more trips than other station pairs. They also found that casual users use bicycles more frequently during midday and the evening, and between stations near recreational land uses (Noland et al. 2016).

# The Data: Panel Study of Emerging Transportation Trends in California

## California Millennials Dataset

The California Millennials Dataset was collected in fall 2015, as part of an on-going research project investigating emerging travel patterns among selected segments of the population in California. The dataset was collected as the first wave of data collection of the *Panel Study of Emerging Technologies and Transportation Trends* in California. During the first phase of this research project, we designed an online survey and administered it to a sample of more than 2400 residents of California that were recruited through an online opinion panel. The sample included 1400 millennials, i.e., young adults 18 to 34 years old in 2015, and 1000 members of the preceding Generation X, i.e., middle-aged adults between 35 and 50 years old.

We employed a quota sampling approach to ensure that a sufficient number of respondents were sampled from each of six main geographic regions of California and from three neighborhood types (urban, suburban, and rural). We defined the six regions as (1) the California Central Valley; (2) Sacramento, following the boundaries of the Sacramento Area Council of Governments (SACOG); (3) San Diego, following the boundaries of the San Diego Association of Governments (SANDAG); (4) Greater Los Angeles, following the boundaries of the Southern California Association of Governments (SCAG); (5) the San Francisco Bay Area, following the boundaries of the Metropolitan Transportation Commission (MTC); and (6) the rest of Northern California and Others, comprising the remaining mountain, coastal and rural regions in the state. Table 1 summarizes the distribution of the 58 California counties included in each region in the study. In addition, we set targets for five socio-demographic characteristics in order to mimic the distribution in the population of California for gender, age, household income, race and ethnicity, and presence of children in the household. After data cleaning and recoding, the final dataset useful for analysis contained 1975 cases.

**Table 1. Regions Included in the Study and Corresponding Metropolitan Planning Organizations (MPOs) and Counties in California**

| Region | MPO | Counties: |
|---|---|---|
| Central Valley | Central Valley | Fresno, Kern, Kings, Madera, Merced, San Joaquin, Stanislaus, Tulare |
| Sacramento | SACOG | El Dorado, Placer, Sacramento, Sutter, Yolo, Yuba |
| San Diego | SANDAG | San Diego |
| Los Angeles | SCAG | Imperial, Los Angeles, Orange, Riverside, San Bernardino, Ventura |
| San Francisco Bay Area | MTC | Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, Sonoma |
| Northern California and Others | NorCal and Others | Alpine, Amador, Butte, Calaveras, Colusa, Del Norte, Glenn, Humboldt, Inyo, Lake, Lassen, Mariposa, Mendocino, Modoc, Mono, Monterey, Nevada, Plumas, San Benito, San Louis Obispo, Santa Barbara, Santa Cruz, Shasta, Sierra, Siskiyou, Tehama, Trinity, Tuolumne |

We employed a combination of cell weighting and iterative proportional fitting (IPF) raking to compensate for the effects of the quota sampling (e.g., with the intentional oversampling of lower-population regions that was made to collect enough respondents to develop robust analyses for all regions of California) and correct for the non-representativeness of the sample on various pertinent traits, including age group, neighborhood type, region, race, ethnicity, presence of children in the household, household income, student/employment status, and gender (for additional details, see Circella et al. 2017b). As part of the activities developed in this part of the project, we further revised and updated the weights by employing standard procedures to improve the distribution and reduce extreme weights through trimming.

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

In addition, the survey asked respondents to report their level of agreement with 66 attitudinal statements on a 5-point Likert-type scale from "Strongly disagree" to "Strongly agree." These questions measured individual attitudes and preferences related to 28 pre-identified general and transportation-related latent constructs including land use preferences, environmental concerns, adoption of technology, government role, travel preferences, car ownership, and others. We performed a principal axis factor analysis with an oblique rotation which reduced the dimensionality from 66 statements to 17 factors and 10 remaining single statements that identified main attitudinal constructs.

In the survey, we asked respondents to indicate whether they are already familiar with various types of emerging shared-mobility services, if these services are available in the area where they live, and what services they have already used. For those services that respondents had already used, they were asked to report how often they use them. The emerging transportation services included in the study were *fleet-based carsharing* (e.g., Zipcar or Car2go), *peer-to-peer carsharing* (e.g., Turo), *ridehailing services* (e.g., Uber or Lyft), *dynamic carpooling* (e.g., Zimride or Carma), *peer-to-peer carpooling* (usually arranged via online platform such as Facebook or Craigslist) and *bikesharing*. In addition to the adoption rate and frequency of use, we asked users of *ridehailing* to rate the importance of a set of factors in affecting their use of these services. Respondents were also asked to report how the use of these services impacted their use of other means of transportation, and what they would have done regarding the last trip they made with on-demand ride services if these services had not been available. For detailed information on the data collection process, the content of the survey, and the exact language used for these questions, see Circella et al. (2016, 2017b).
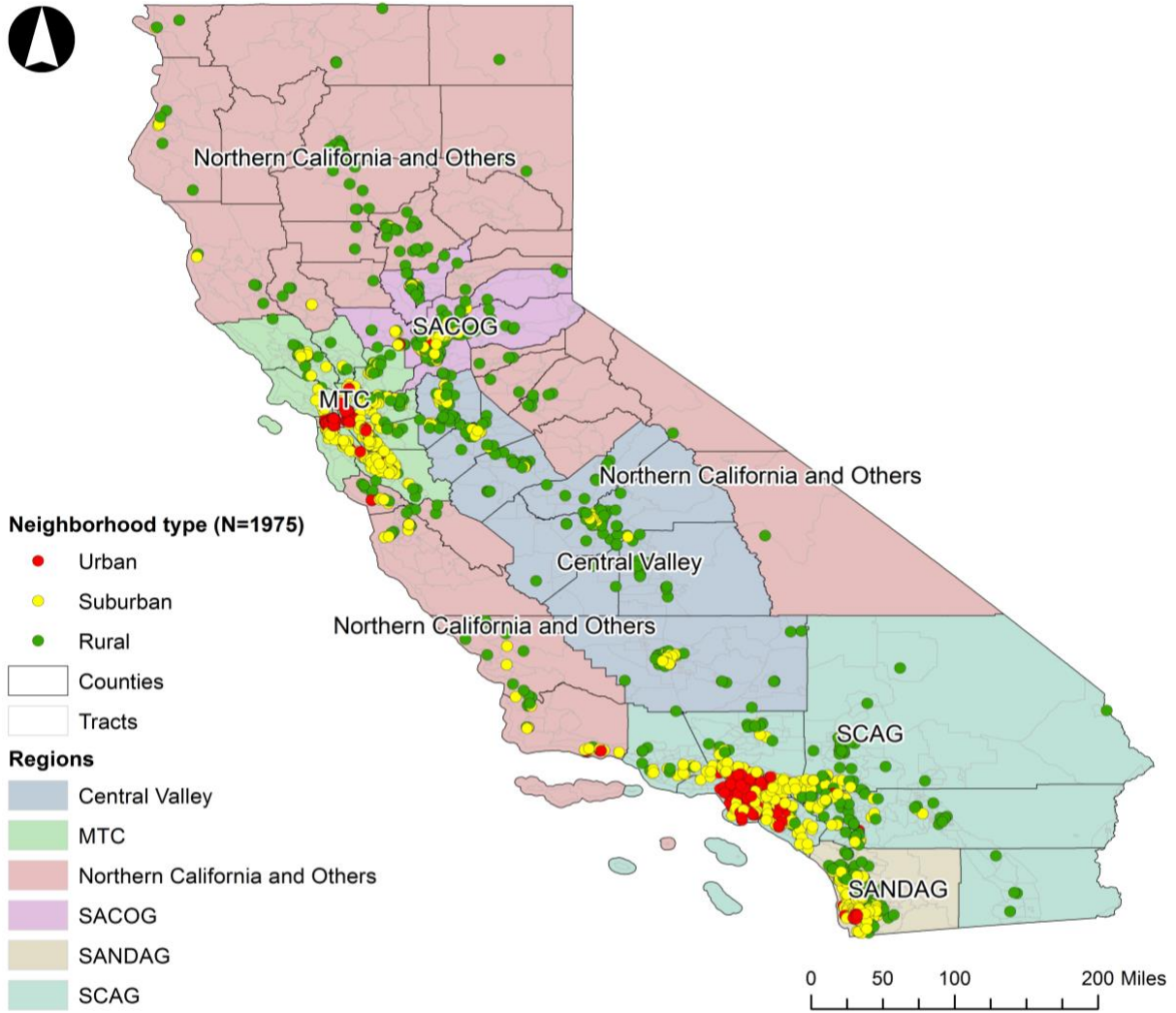
**Figure 1. Distribution of respondents by neighborhood type and region of California**

**Table 2. Descriptive Statistics for the California Millennials Dataset (N = 1975, Weighted Sample)**

| | Dependent Millennials | | Independent Millennials | | Gen Xers | |
|---|---|---|---|---|---|---|
| | Number of cases | Percent of total | Number of cases | Percent of total | Number of cases | Percent of total |
| *Sociodemographics* | | | | | | |
| **Age** | | | | | | |
| 18 to 24 | 217 | 62.4% | 221 | 31.3% | | |
| 25 to 34 | 131 | 37.6% | 485 | 68.7% | | |
| 35 to 44 | | | | | 632 | 68.7% |
| 45 to 50 | | | | | 289 | 31.3% |
| | | | | | | |
| **Gender** | | | | | | |
| Female | 167 | 47.8% | 374 | 53.0% | 473 | 51.4% |
| Male | 182 | 52.2% | 331 | 47.0% | 447 | 48.6% |
| | | | | | | |
| **Income** | | | | | | |
| Less than $20,000 | 24 | 7.0% | 96 | 13.6% | 55 | 6.0% |
| $20,001 to $40,000 | 68 | 19.6% | 160 | 22.7% | 126 | 13.7% |
| $40,001 to $60,000 | 58 | 16.6% | 108 | 15.3% | 111 | 12.0% |
| $60,001 to $80,000 | 60 | 17.3% | 85 | 12.0% | 126 | 13.7% |
| $80,001 to $100,000 | 23 | 6.6% | 61 | 8.6% | 97 | 10.5% |
| $100,001 to $120,000 | 24 | 6.8% | 66 | 9.3% | 110 | 11.9% |
| $120,001 to $140,000 | 12 | 3.3% | 42 | 6.0% | 57 | 6.2% |
| $140,001 to $160,000 | 13 | 3.8% | 25 | 3.6% | 72 | 7.8% |
| More than $160,000 | 27 | 7.8% | 31 | 4.4% | 114 | 12.4% |
| Prefer not to answer | 39 | 11.2% | 32 | 4.5% | 52 | 5.7% |

NCST

| | Dependent Millennials | | Independent Millennials | | Gen Xers | |
|---|---|---|---|---|---|---|
| | Number of cases | Percent of total | Number of cases | Percent of total | Number of cases | Percent of total |
| **Race** | | | | | | |
| African American or Black | 11 | 3.0% | 18 | 2.5% | 50 | 5.4% |
| American Indian, Eskimo, or Aleut | 15 | 4.4% | 22 | 3.1% | 14 | 1.5% |
| Asian or Pacific Islander | 54 | 15.6% | 94 | 13.3% | 157 | 17.0% |
| Caucasian or White | 168 | 48.0% | 423 | 59.9% | 571 | 62.0% |
| Multiethnic or multicultural | 49 | 14.0% | 66 | 9.4% | 53 | 5.7% |
| Other ethnic background | 52 | 15.0% | 84 | 11.8% | 77 | 8.3% |
| **Ethnicity** | | | | | | |
| Hispanic | 187 | 53.6% | 310 | 43.9% | 310 | 33.6% |
| Not Hispanic | 162 | 46.4% | 396 | 56.1% | 611 | 66.4% |
| **Lives with Children** | | | | | | |
| Yes | 141 | 40.4% | 329 | 46.6% | 561 | 61.0% |
| No | 208 | 59.6% | 377 | 53.4% | 359 | 39.0% |
| **Lives with Parents** | | | | | | |
| Yes | 349 | 100.0% | | 0.0% | 94 | 10.3% |
| No | | 0.0% | 706 | 100.0% | 826 | 89.7% |
| **Education** | | | | | | |
| Some grade/high school | 18 | 5.0% | 6 | 0.8% | 6 | 0.6% |
| High school/GED | 67 | 19.1% | 91 | 12.9% | 74 | 8.1% |
| Some college/technical school | 147 | 42.3% | 14 | 2.0% | 207 | 22.5% |
| Associate's degree | 24 | 6.8% | 77 | 10.9% | 114 | 12.3% |
| Bachelor's degree | 74 | 21.1% | 241 | 33.9% | 334 | 36.3% |
| Graduate degree (e.g., MS, PhD, etc.) | 9 | 2.6% | 70 | 9.8% | 125 | 13.6% |
| Professional degree (e.g., JD, MD, etc.) | 5 | 1.3% | 187 | 26.3% | 59 | 6.4% |
| Prefer not to answer | 6 | 1.8% | 25 | 3.5% | 2 | 0.2% |

NCST

| | Dependent Millennials | | Independent Millennials | | Gen Xers | |
|---|---|---|---|---|---|---|
| | Number of cases | Percent of total | Number of cases | Percent of total | Number of cases | Percent of total |
| **Neighborhood Type** | | | | | | |
| Rural | 111 | 32.0% | 167 | 23.6% | 259 | 28.1% |
| Suburban | 176 | 50.6% | 304 | 43.1% | 426 | 46.3% |
| Urban | 61 | 17.5% | 235 | 33.3% | 235 | 25.5% |
| | | | | | | |
| **Neighborhood Type Where Grew Up** | | | | | | |
| Rural | 13 | 3.9% | 58 | 8.2% | 65 | 7.0% |
| Small town | 31 | 8.9% | 99 | 14.0% | 81 | 8.8% |
| Suburban | 189 | 54.2% | 330 | 46.7% | 474 | 51.5% |
| Urban | 115 | 33.1% | 219 | 31.0% | 301 | 32.7% |
| | | | | | | |
| **Use of Uber/Lyft** | | | | | | |
| Never | 286 | 82.0% | 468 | 66.3% | 747 | 81.2% |
| Less than once a Month | 43 | 12.5% | 115 | 16.3% | 107 | 11.6% |
| More than Once a Month | 19 | 5.6% | 123 | 17.5% | 66 | 7.2% |
| | | | | | | |
| **Use of Carsharing** | | | | | | |
| Never | 333 | 95.4% | 669 | 94.8% | 905 | 98.3% |
| Less than once a Month | 13 | 3.6% | 18 | 2.6% | 12 | 1.3% |
| More than Once a Month | 4 | 1.0% | 19 | 2.6% | 3 | 0.3% |

NCST

## Future waves of data collection in the panel

In the next stage of the panel study, we plan to develop the longitudinal component of the research through a second wave of data collection in early 2018 that will be integrated with the 2015 California Millennials Dataset. Turning the project into a longitudinal study with a *rotating panel* structure allows us to harvest the full potential of this research program. During the next stage of the project, we also plan to broaden the research beyond the generational groups of millennials and Gen Xers, expanding the data collection to the entire population of adults in California, e.g., including the sizable group of baby boomers and the members of the younger Generation Z who have already turned 18 in the study.

We plan to use a combination of sampling strategies for the second wave of data collection, including the use of the same online opinion panel used for the first round of data collection and the distribution of a paper version of the survey to be mailed to a random sample of respondents in the state, in order to expand the target population of the study, and reach segments, e.g., elderly or people that are not familiar with technology, who would not be well represented in an online survey. We plan to recall the respondents that completed the 2015 survey using the same online opinion panel, where we expect to be able to retain close to 50% of the respondents from 2015 (e.g., approx. 1,000 respondents in Sample A). In addition, we will *refresh* the panel adding a group of participants in this wave of data collection (similarly, for future waves of data collection in this panel study, we will continue to refresh the panel at each round of data collection with a similar approach). Thus, we plan to include an additional group of participants (Sample B, with a target of 1,000 individuals) which will be sampled with a methodology similar to the original 2015 data collection. Sample B will allow refreshing the panel with new members that will be included in the research, and also allow expanding the age cohorts in the study (including *young* respondents aka members of Generation Z, currently between 18 and 21, and baby boomers who were not included in the data collection in 2015).

The comparison of the characteristics (and behaviors) of the individuals in the Sample A and Sample B, who are recruited with the same methodology (in addition to the comparison of the individuals in the Sample A and in the original dataset from 2015) will allow us to evaluate the potential self-selection bias associated with the respondents in Sample A that decide to continue to opt in and remain part of the panel study, and compare the characteristics and behaviors of the members in the different groups. Finally, through the creation of a paper version of the survey which we will send to a random sample of addresses in the state, we plan to recruit a third Sample C of participants (with a random sampling) and further expand the target population of the study. This approach will allow us to reach additional segments of the population, e.g., elderly or people that are not familiar with technology, who are less likely to be part of an online opinion panel and would not be well represented in an online survey. Figure 2 summarizes the sampling strategy for the second wave of data collection in the panel study. The expected sample size for this wave of data collection (including all three subsamples A, B and C) is 3,000.

In the new Phase II survey, we plan to collect information for additional types of shared mobility services that have been introduced during recent years, specifically *pooled ridehailing* services such as UberPOOL or Lyft Line. The impact of the use of these services (e.g., in terms of vehicle miles traveled or greenhouse gas emissions) may differ significantly from that of other shared mobility services. Similarly, we plan to introduce another section on autonomous vehicles (AVs), to collect information about perceptions and propensity to adopt AVs, eventually also through a model of shared-ownership/shared-use.
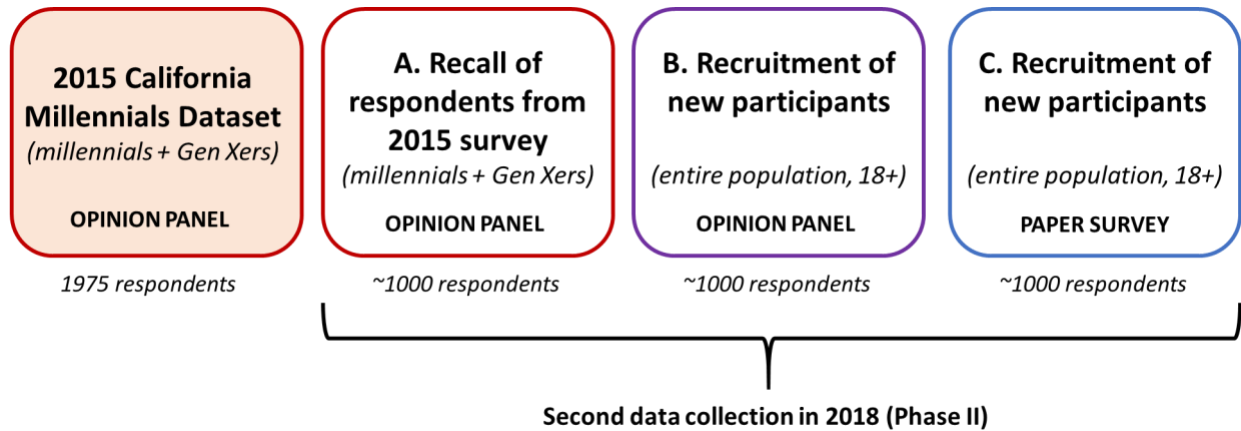


**Figure 2. Sampling strategy for second round of data collection in Phase II of the research**

The panel study will provide a unique opportunity to study the impacts of emerging technologies and trends with longitudinal data. It will allow us to disentangle the role of stage in life in affecting lifestyles and travel decisions, better evaluate the impacts of the *lifecycle*, *periods* and *generational* effects, and investigate the complex relationships behind the formation of travel behavior over time (e.g., modifications in the use of shared mobility and their impacts on vehicle ownership) among the various segments of the population.

# Adoption and Frequency of Use of Shared Mobility Services

In this section, we explore the use of shared mobility services among the members of the different generation groups. We start our analysis computing descriptive statistics for the awareness, availability and frequency of use of the various types of services that were included in this study. The following sections focus on estimating models that explore the relationships behind the use of these services, and investigate the factors that affect the adoption, frequency of use and the impacts that these services have on other components of travel behavior.

## Descriptive statistics

### Uber/Lyft

The percentage of respondents that are aware of and use ridehailing varies by region. The majority of respondents from all regions say that they have heard of Uber/Lyft (Figure 3 and Figure 4). The respondents from San Francisco Bay Area and Los Angeles have the highest percentages of use in their hometown or city.



**Figure 3. Awareness and use of ridehailing (Uber/Lyft) by region (total N = 1966, weighted dataset)**
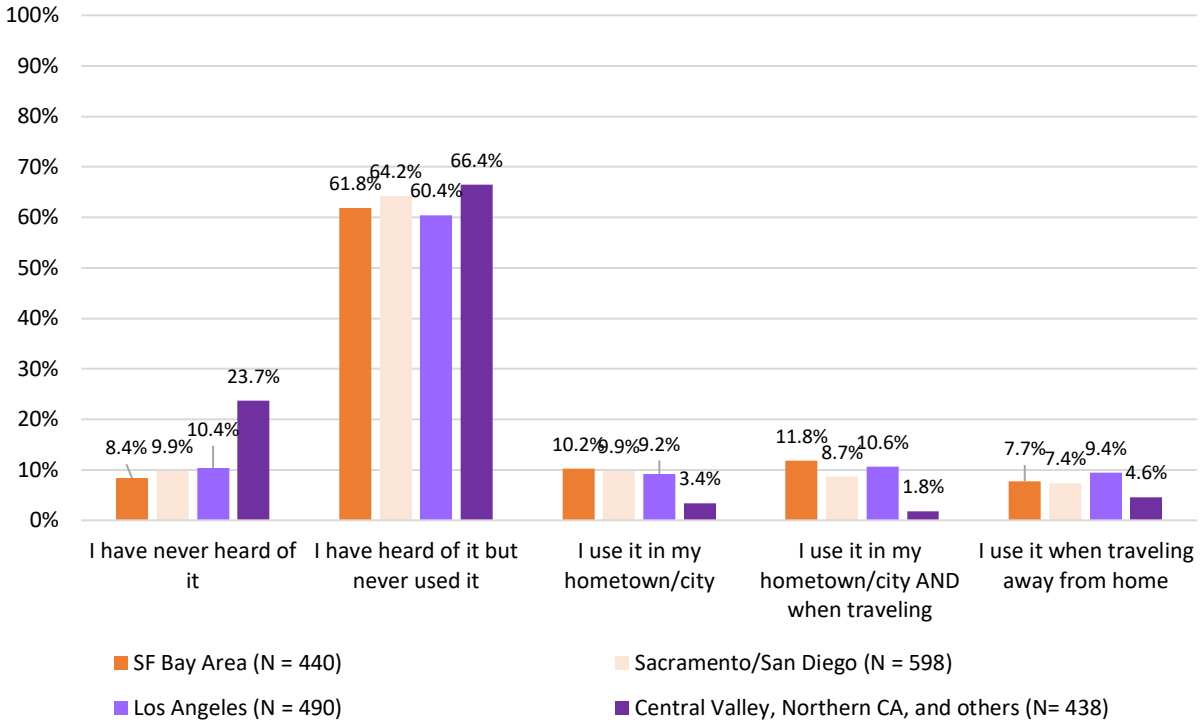
**Figure 4. Awareness and use of ridehailing (Uber/Lyft) by region (total N = 1966, unweighted dataset)**

The level of awareness of the services and the adoption of Uber/Lyft also vary by generation. A higher percentage of millennials in our weighted dataset use Uber/Lyft in their hometown and/or when traveling than Generation X (Figure 5).
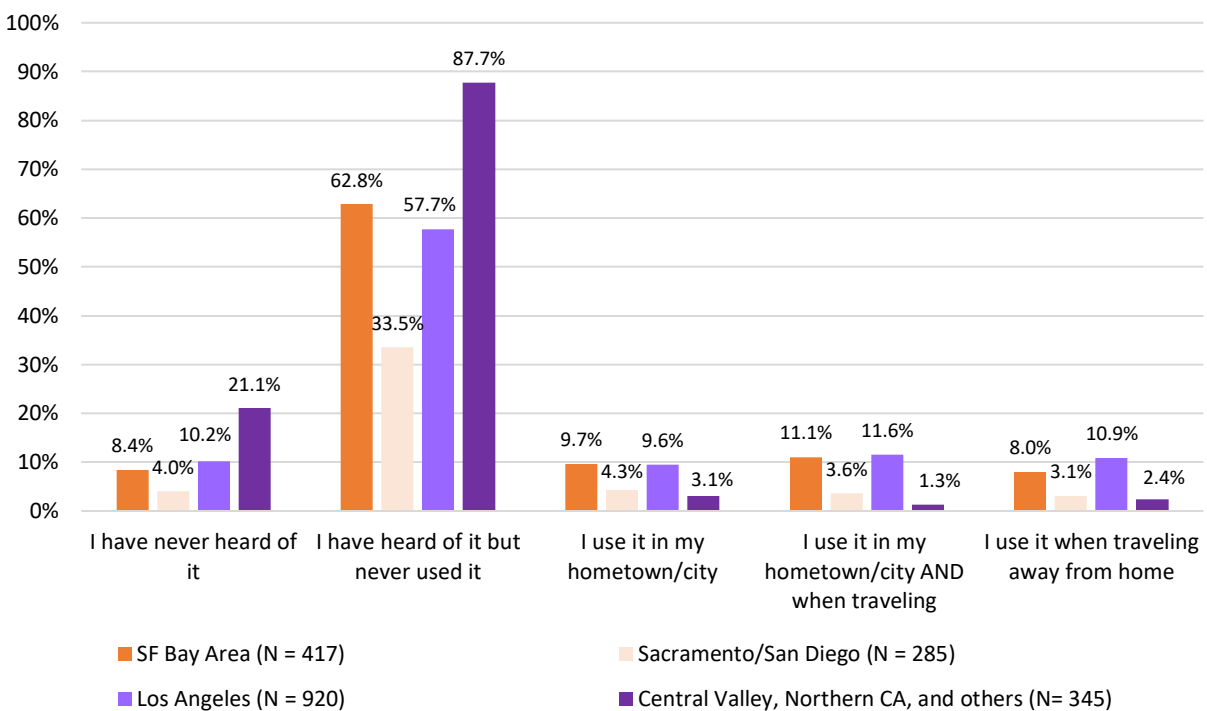
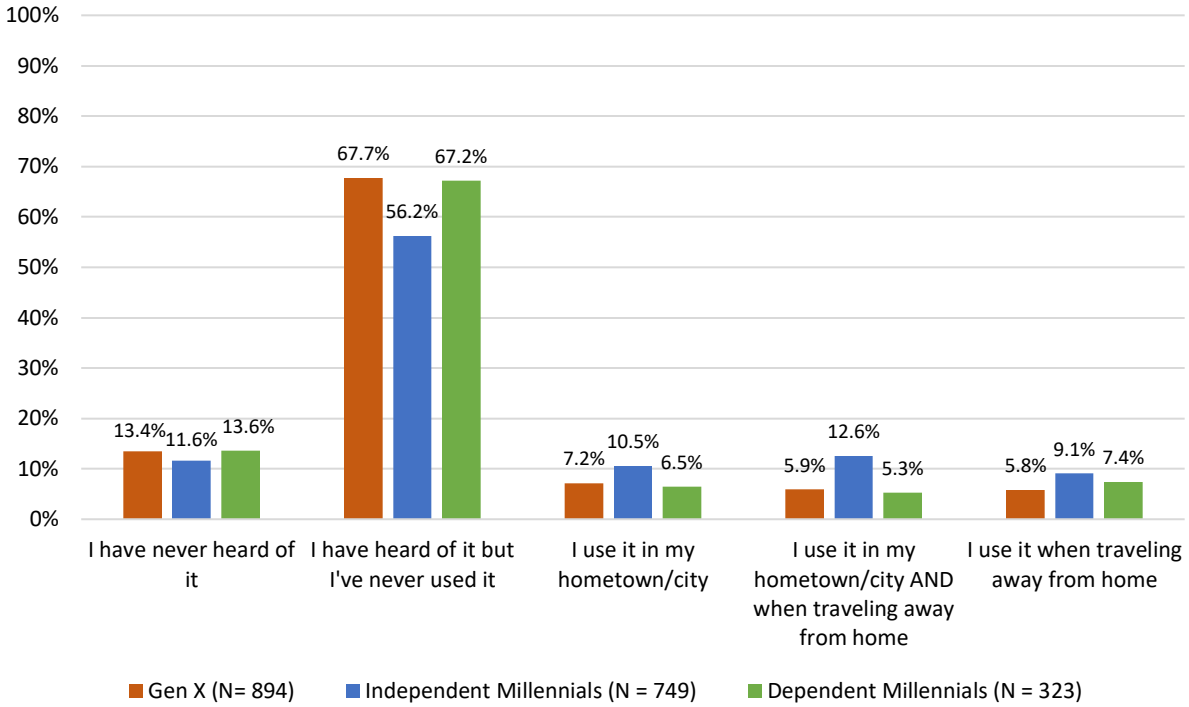**Figure 5. Awareness and use of ridehailing (Uber/Lyft) by generation (N = 1966, unweighted dataset)**
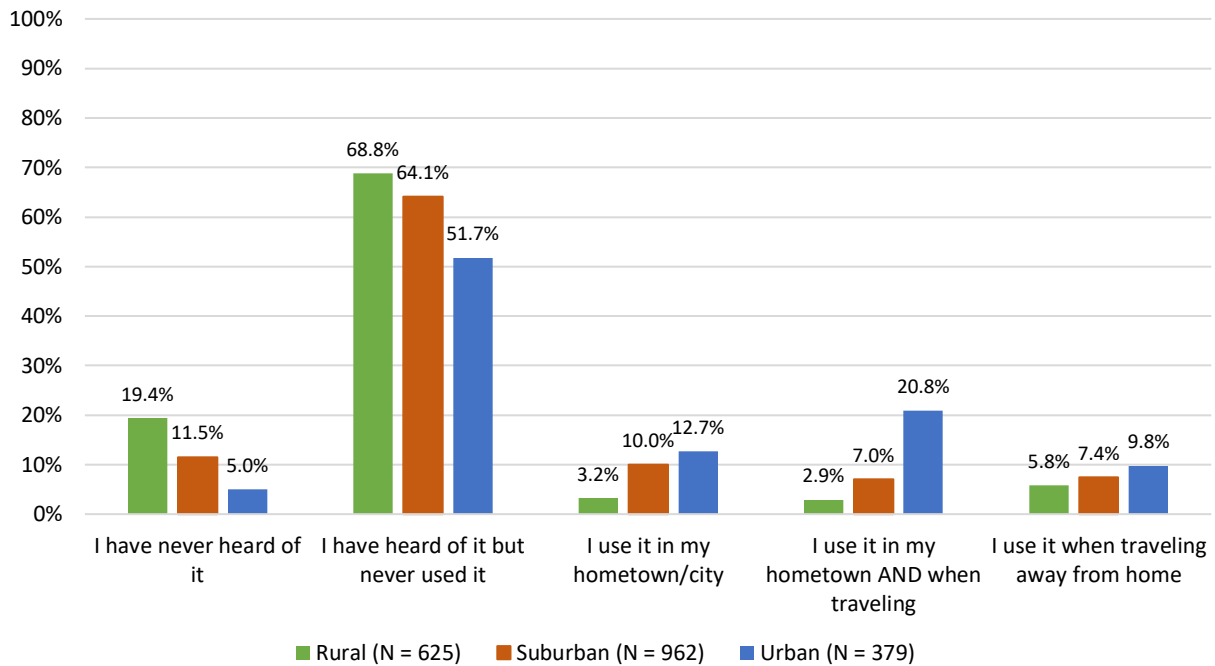


**Figure 6. Awareness and use of ridehailing (Uber/Lyft) by neighborhood type (N = 1966, unweighted dataset)**

Unsurprisingly, respondents who live in urban areas report higher use of Uber/Lyft both when traveling and when in their hometown. A rather high percentage of suburban respondents (10%) also reports that they use Uber/Lyft in their hometown. The majority of rural respondents state that they have heard of Uber/Lyft, but have not used the service, although 6% have used it when traveling away from home (Figure 6).

The following figures report the perceived availability of Uber/Lyft in the city of residence (among those that have not already used the service in their hometown). Twenty two percent of respondents from Northern California and other areas outside the four large metropolitan areas of California said that Uber and Lyft were not available in their area.
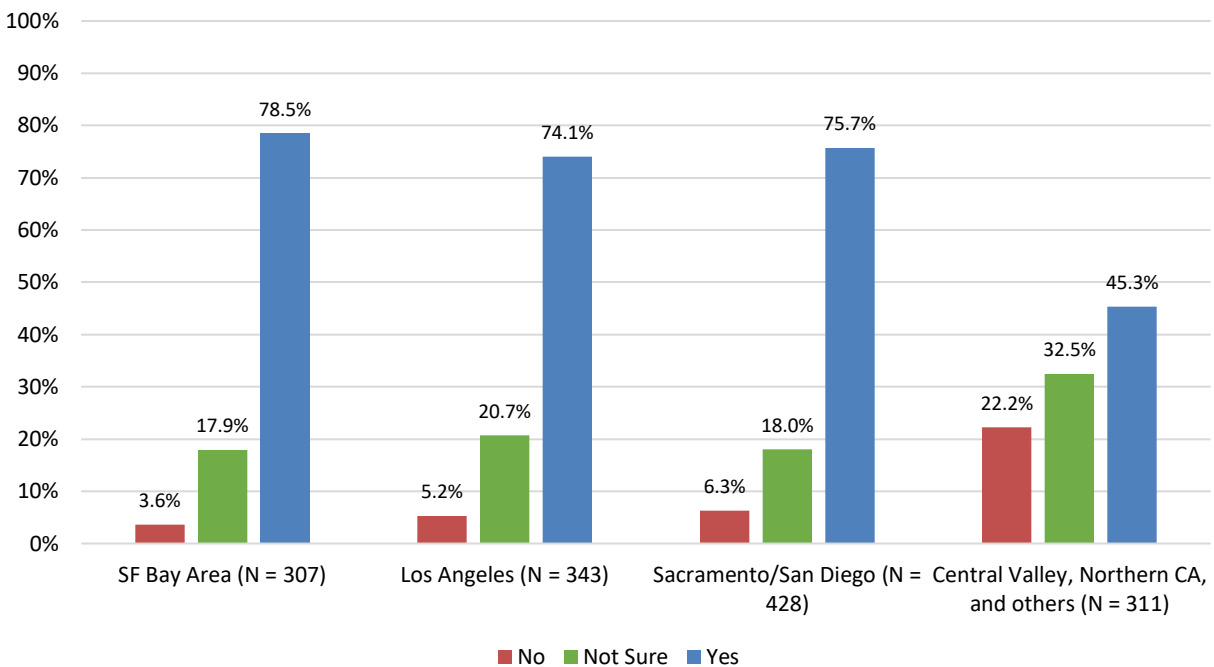


**Figure 7. Perception of ridehailing (Uber/Lyft) availability by region (N = 1389, unweighted dataset)**

Eighty-five percent of urban respondents say that ridehailing is available in their city/ hometown, while 78% of suburban respondents also say that Uber/Lyft are available where they live.
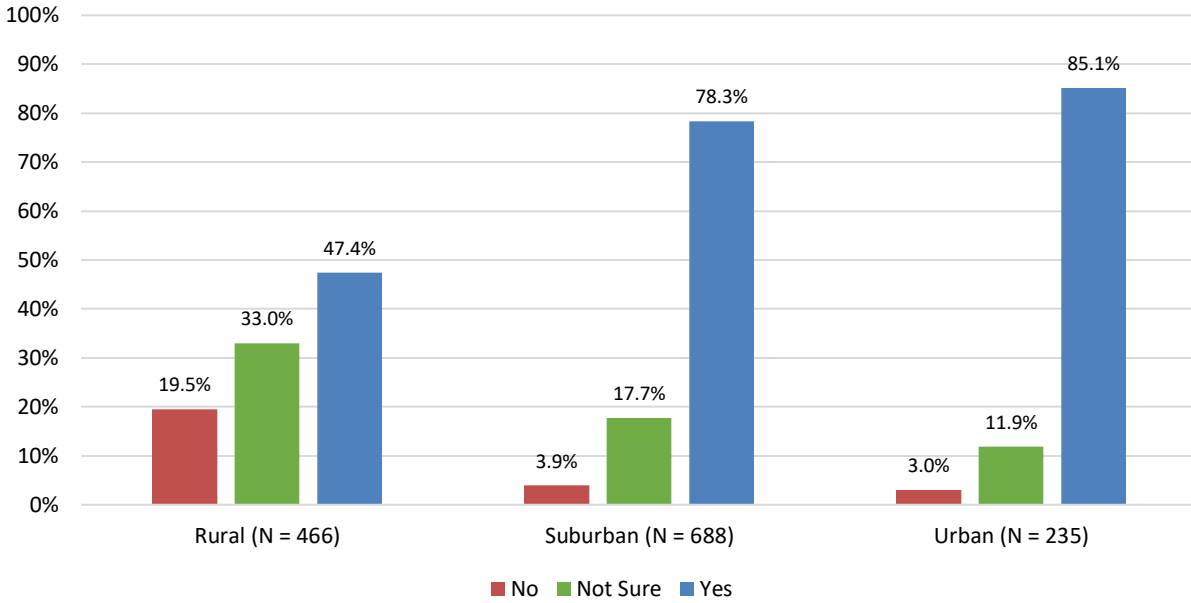
**Figure 8. Perception of ridehailing (Uber/Lyft) availability by neighborhood type (N = 1389, unweighted dataset)**
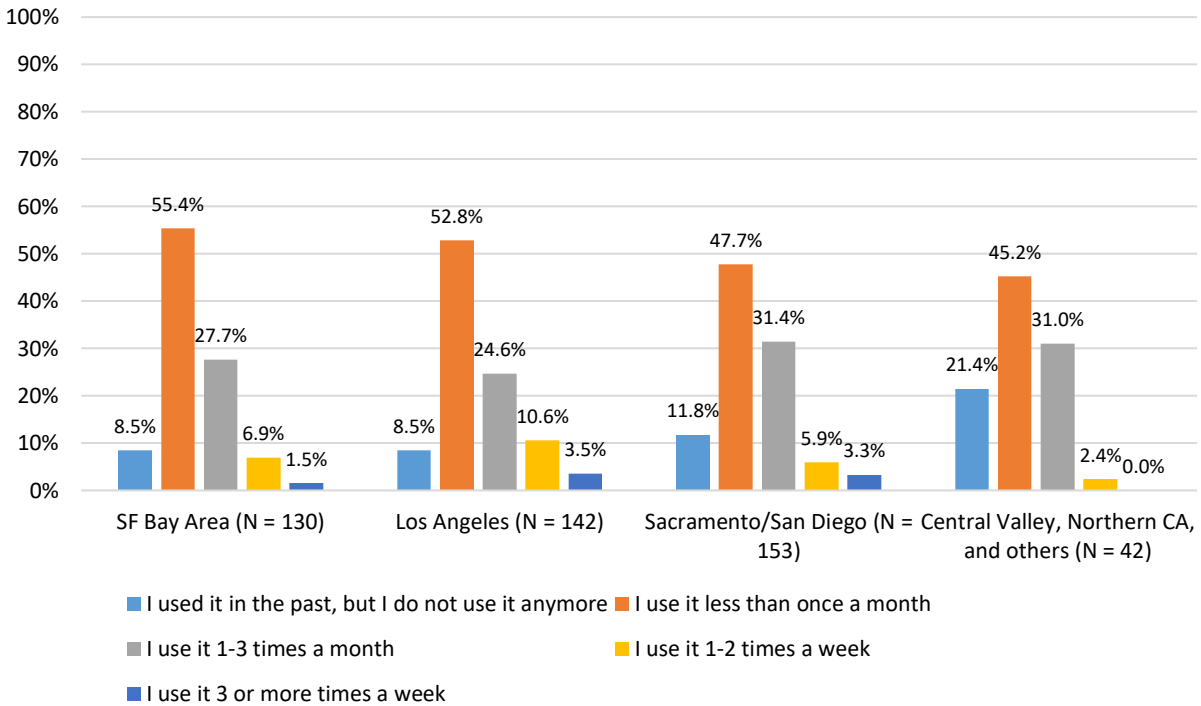


**Figure 9. Frequency of use of ridehailing by region (N = 467, unweighted dataset)**
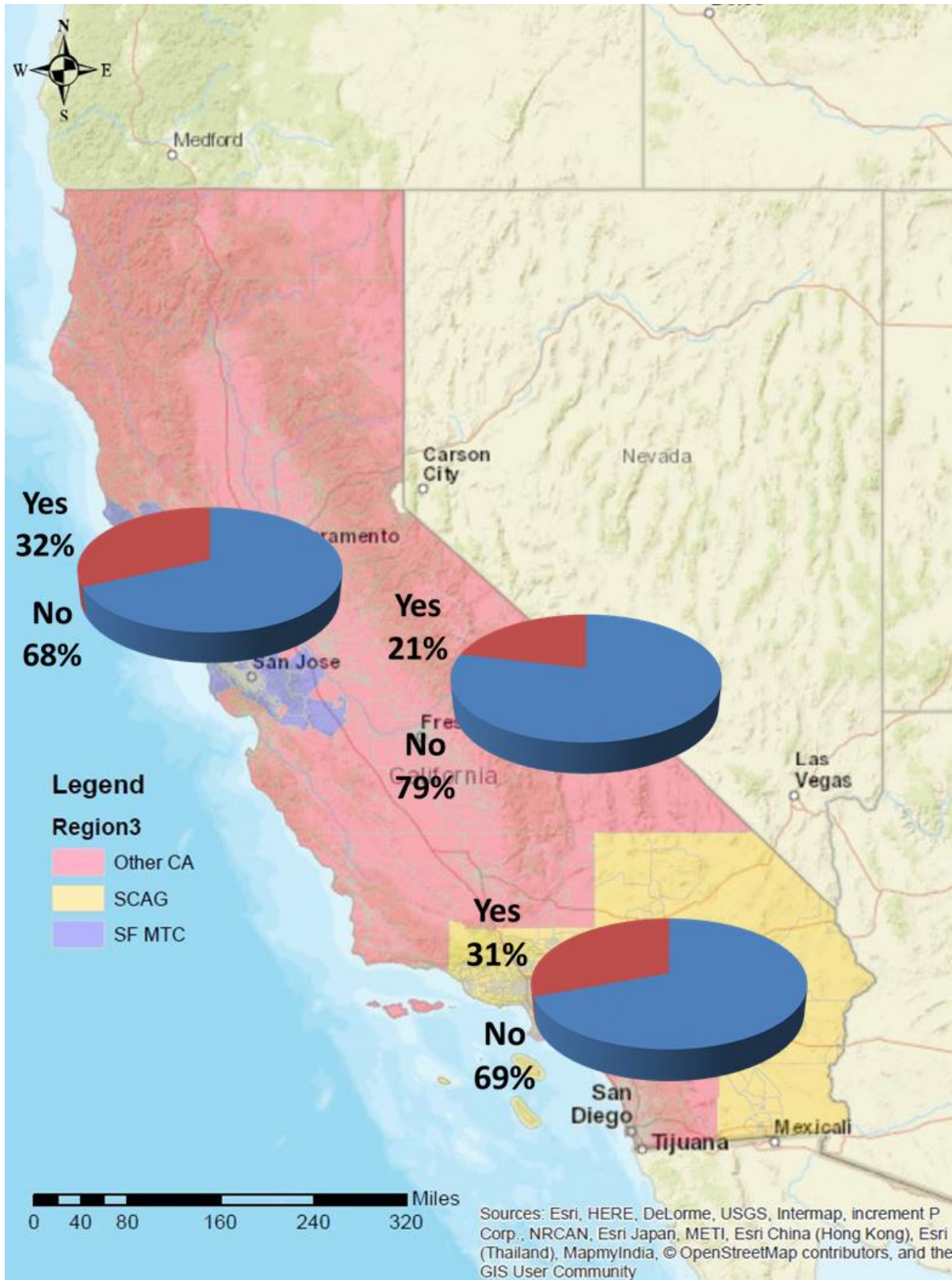
**Figure 10. Adoption of ridehailing by major region of California (N=1707, unweighted dataset)**
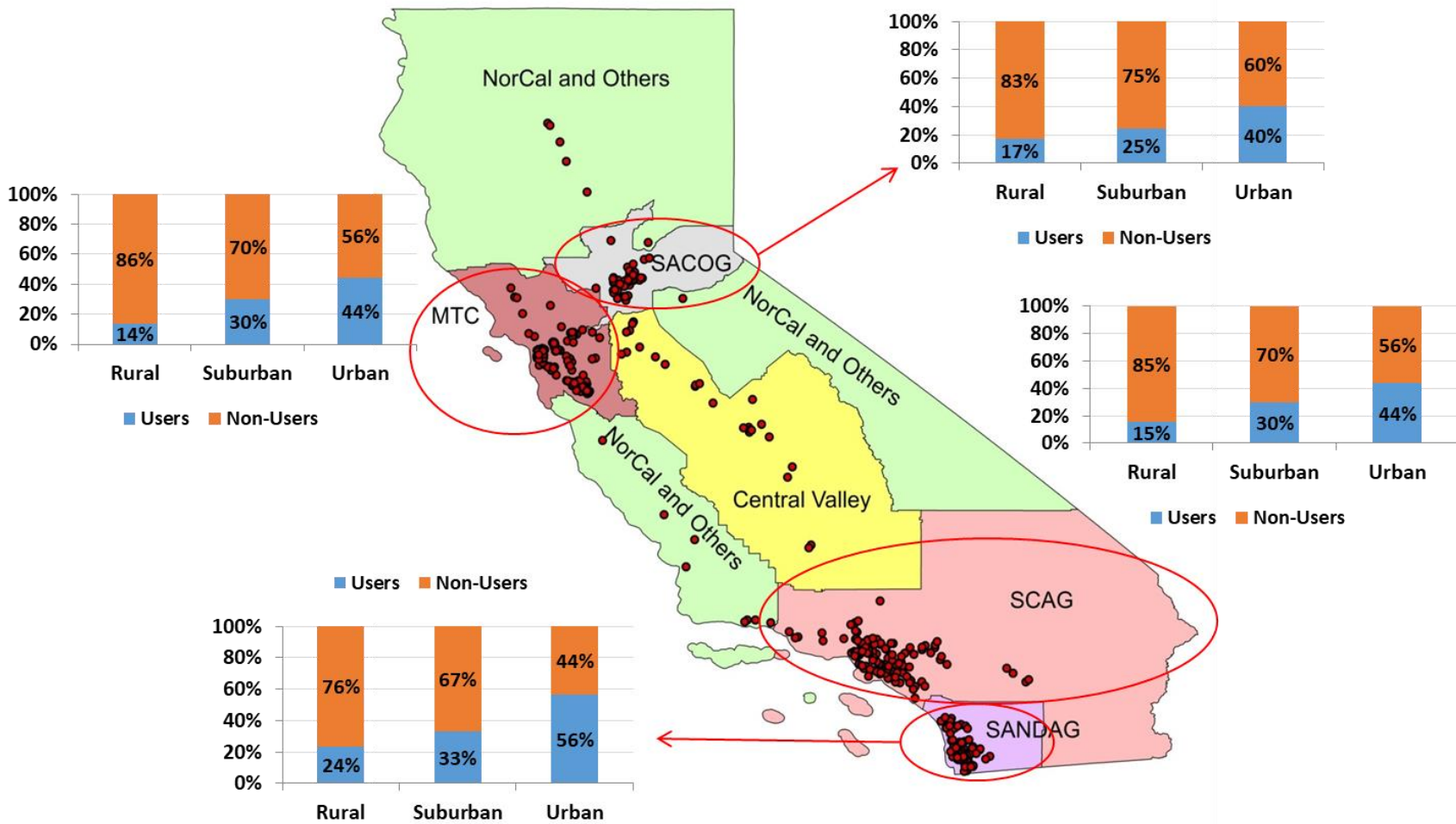
**Figure 11. Adoption of ridehailing by region of California and neighborhood type (N=1707, unweighted dataset)**
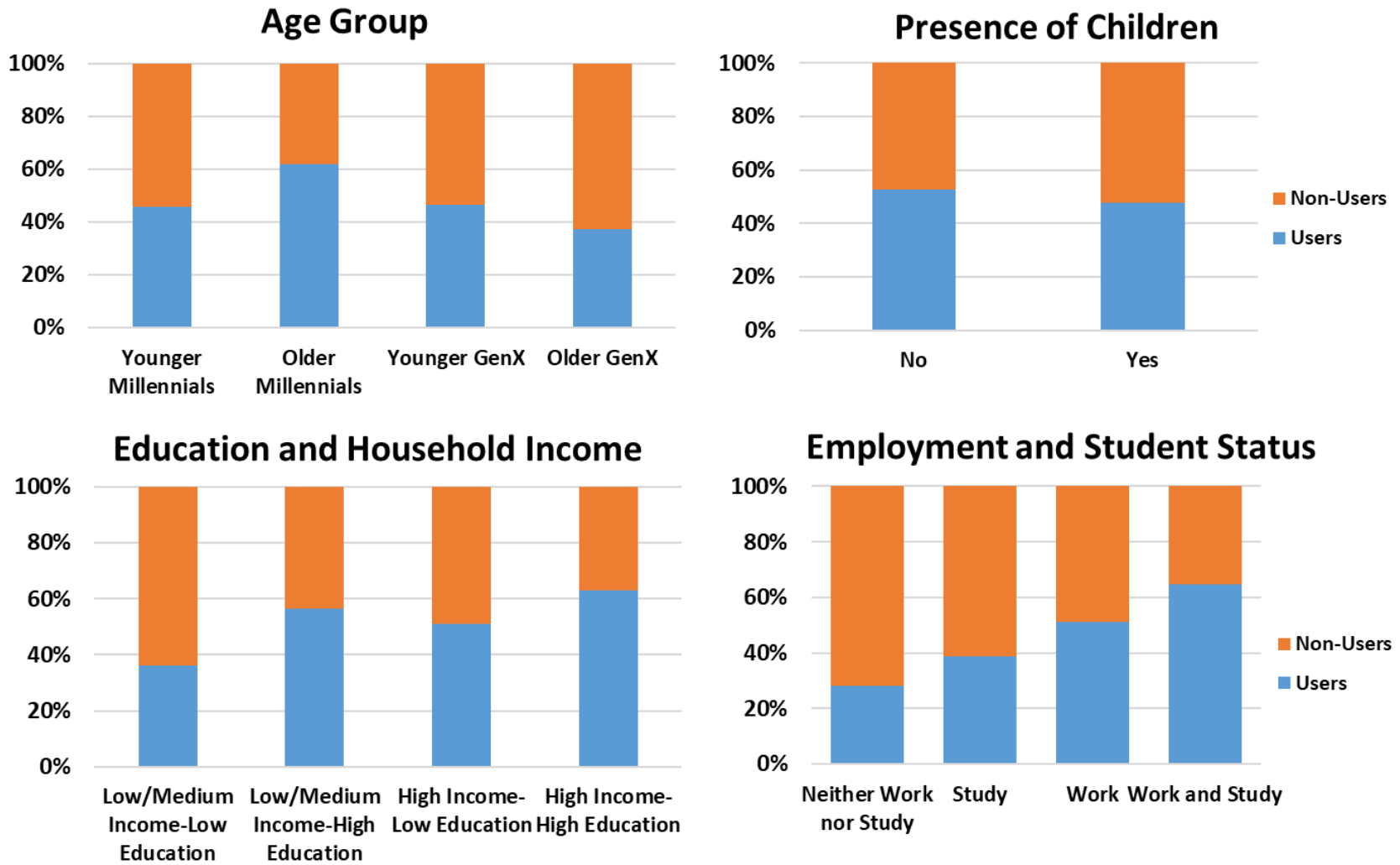
**Figure 12. Adoption of ridehailing by selected sociodemographic characteristics (N=1707, unweighted dataset)**

Los Angeles had the highest percentage of respondents who reported using ridehailing 1-2 times per week or more (14%). Rather small percentages of respondents in each region stated that they use Uber/Lyft very frequently (3 or more times a week).

While generally less than 2% of respondents in the sample used ridehailing 3 or more times a week, 19% of urban respondents reported using ridehailing at least 1-2 times a week, with an additional 33% reporting that they used it 1-3 times a month.

### Carsharing

This section discusses respondents' awareness and use of carsharing services, including services provided by Zipcar as well as other providers, in addition to the perceived availability of these services in their hometowns.

The majority of respondents from each region reported that they had heard of carsharing, but had never used it (54%-72%). The San Francisco Bay Area had the highest percent of respondents (5%) who reported that they use carsharing in their hometown. In contrast to ridehailing, very small percentages of survey respondents from each region report that they use carsharing when traveling away from home (1%-3% versus 3%-11%).
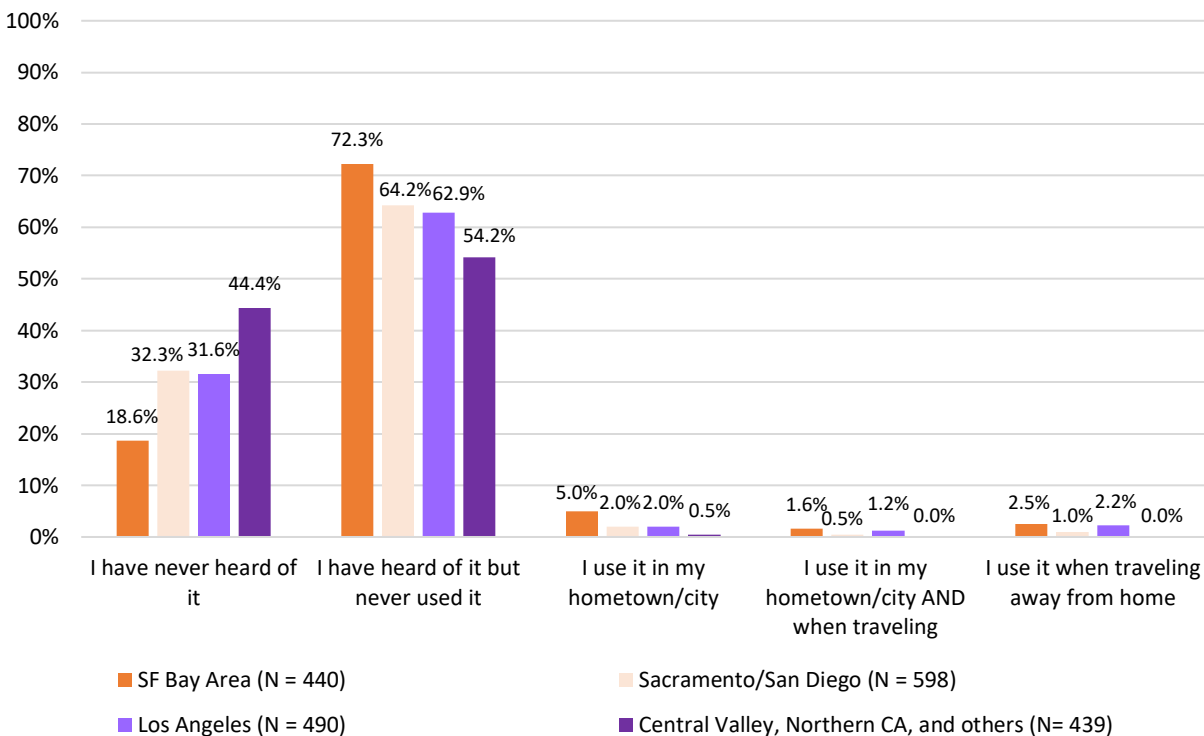


**Figure 13. Knowledge and frequency of use of carsharing services by region (N = 1967, unweighted dataset)**
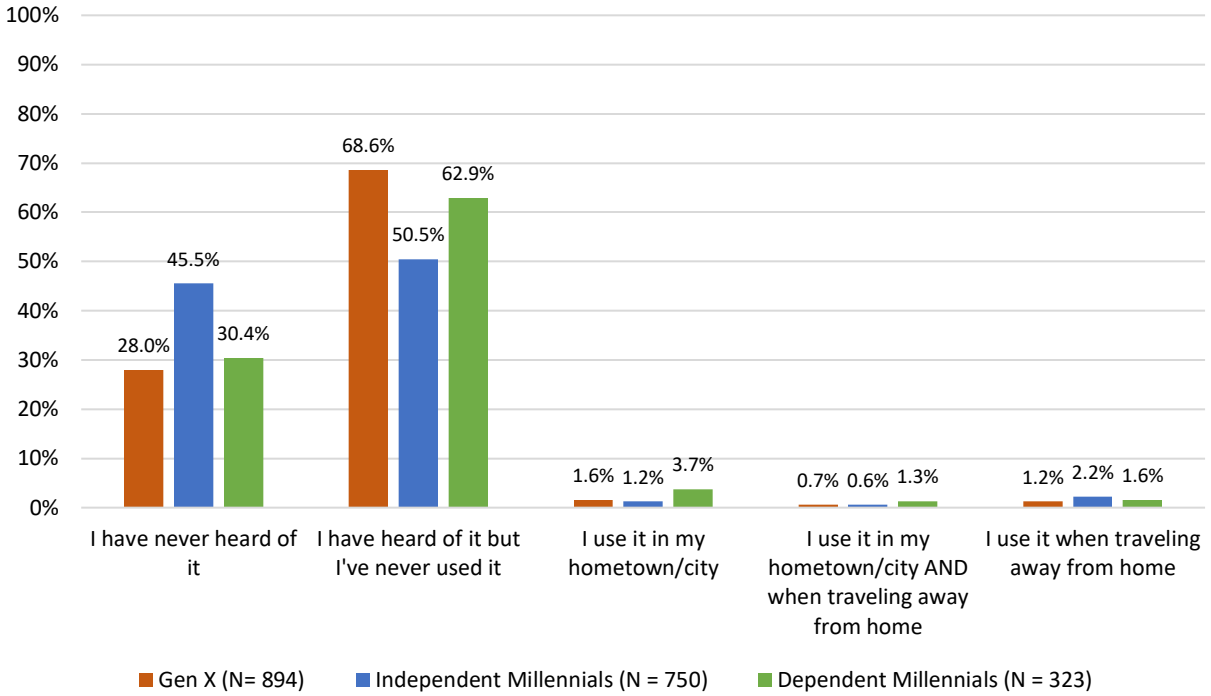
**Figure 14. Awareness and use of carsharing by generation (N = 1967, unweighted dataset)**
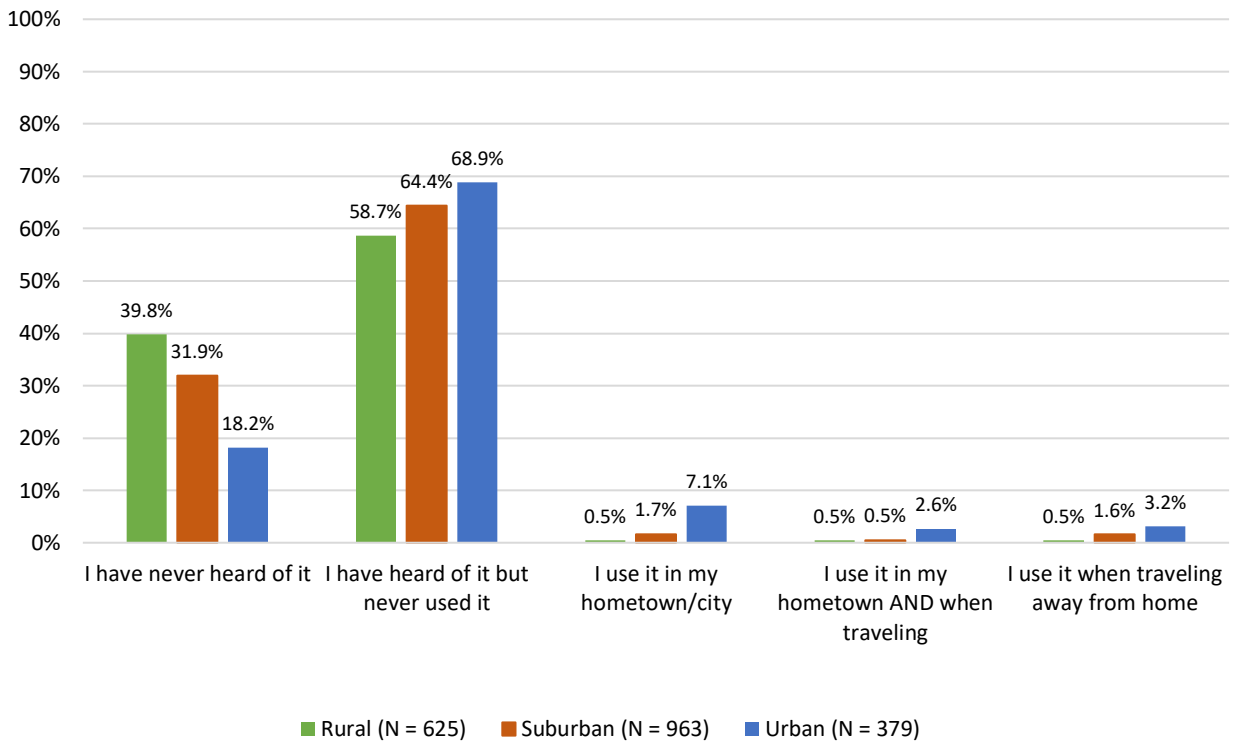


**Figure 15. Knowledge and frequency of use of carsharing services by neighborhood type (N = 1967, unweighted dataset)**

Respondents perceive lower availability of carsharing than ridehailing. Among the users that have never used the service in their hometown, the percentage of respondents that report that carsharing is available where they live is comprised between 17% and 56%.
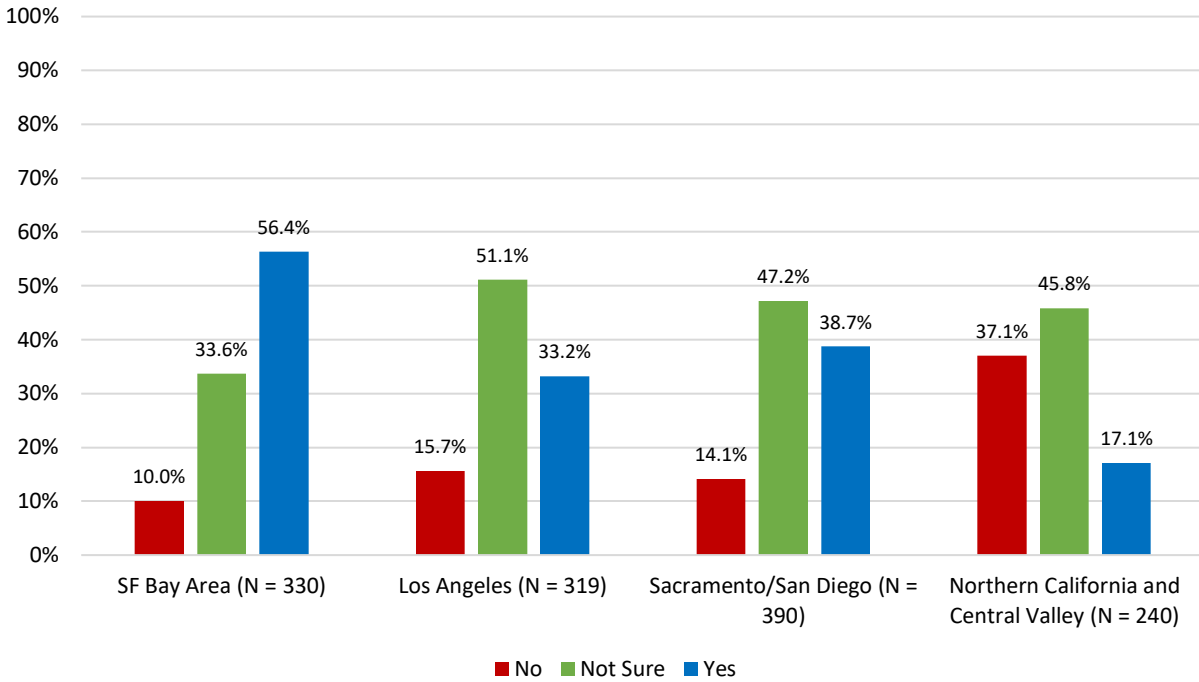


**Figure 16. Perceived availability of carsharing by region (N = 1279, unweighted dataset)**
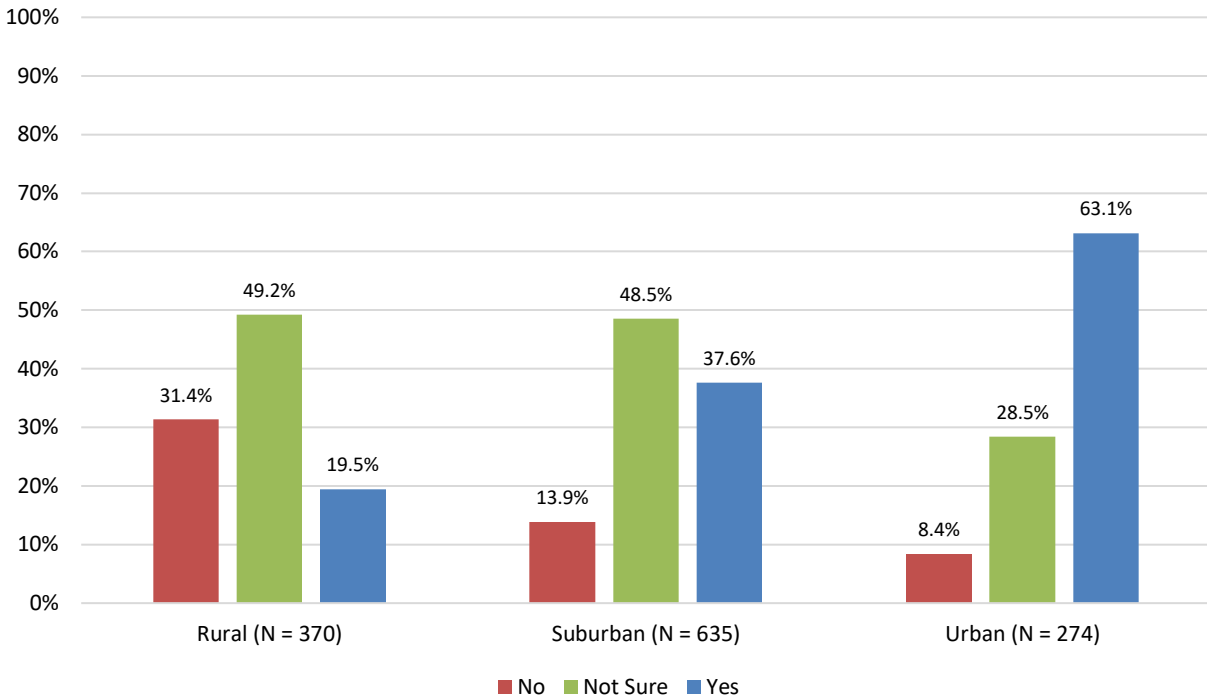
**Figure 17. Perceived availability of carsharing by neighborhood type (N = 1279 unweighted dataset)**

No respondents in our study report using carsharing 5 or more times a week, and less than one percent report using it 3-4 times a week. The majority of urban respondents who use carsharing state that they use it less than once a month (45%), with 19% saying they use it 1-3 times a month.

## Bikesharing

Few respondents said they used bikesharing frequently. The majority of respondents in our survey said that they had either never heard of bikesharing, or had heard of it but never used it. A small percentage of respondents reported using it in their hometown and while traveling. Urban residents had the highest percentage of reported use, both at home and when traveling away from home.
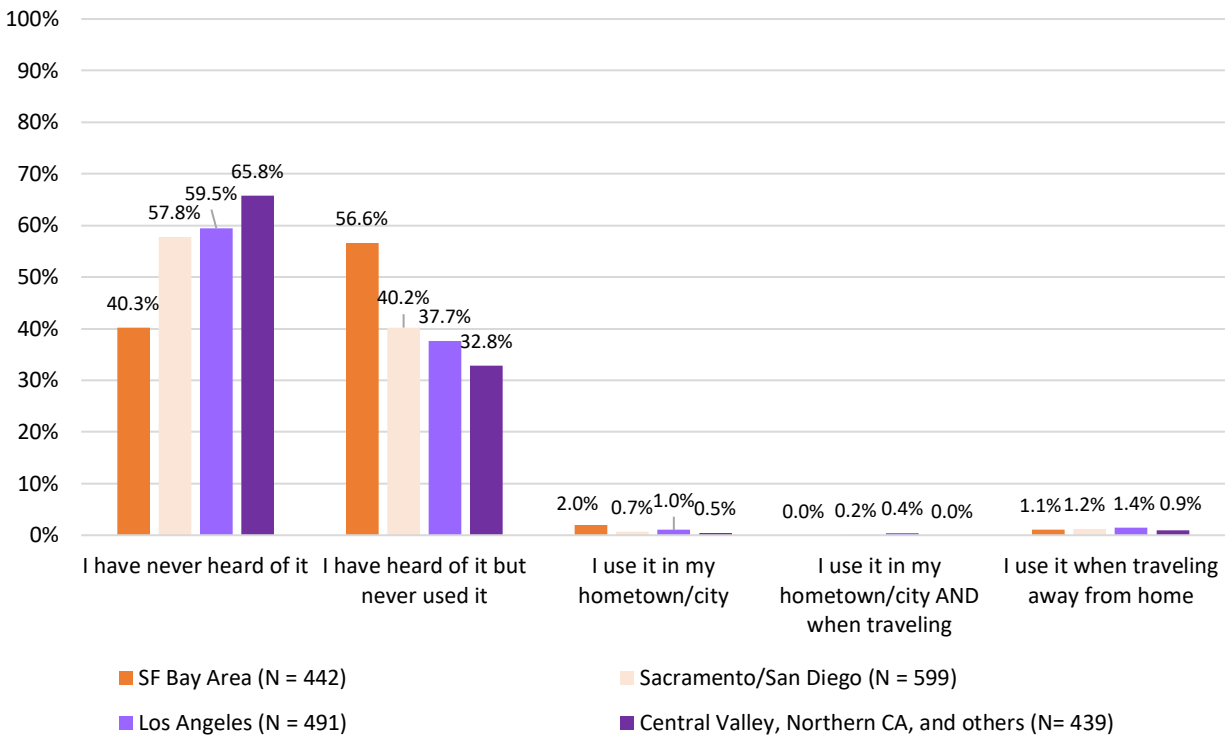


**Figure 18. Awareness and use of bikesharing by region (N = 1971, unweighted dataset)**

The San Francisco Bay Area has the highest percentage of respondents who have heard of bikesharing, while the regions containing Northern California and the Central Valley had the highest percentage that had never heard of the service.
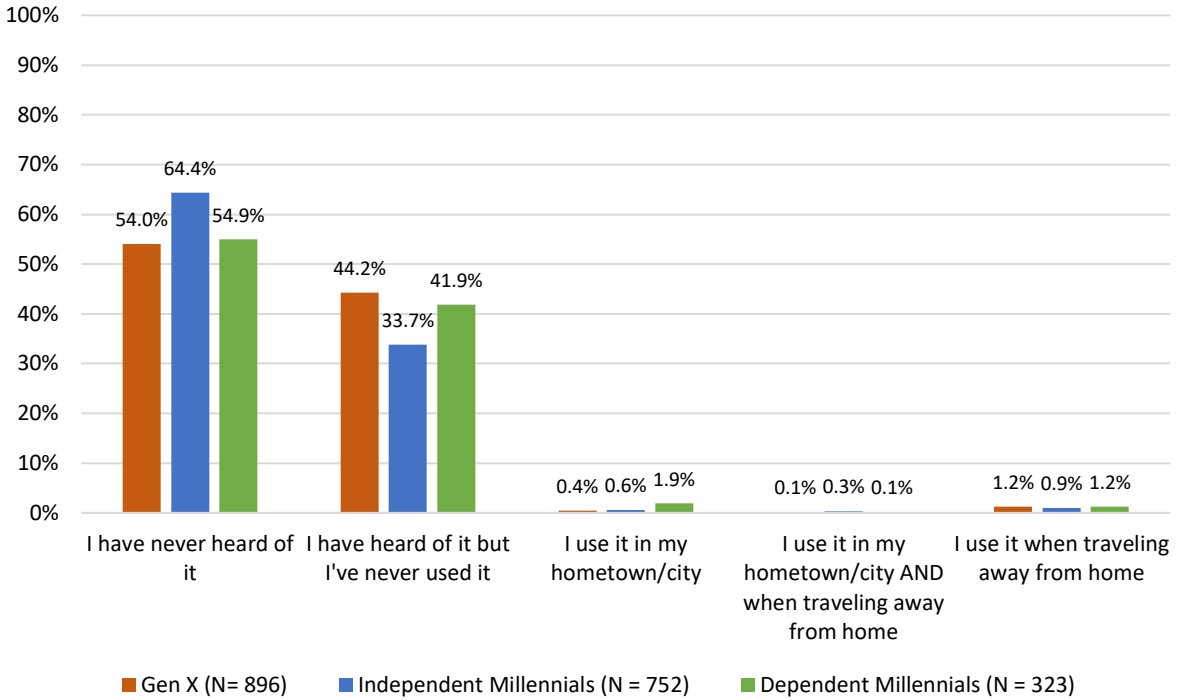
**Figure 19. Awareness and use of bikesharing by generation (total N = 1971, unweighted dataset)**
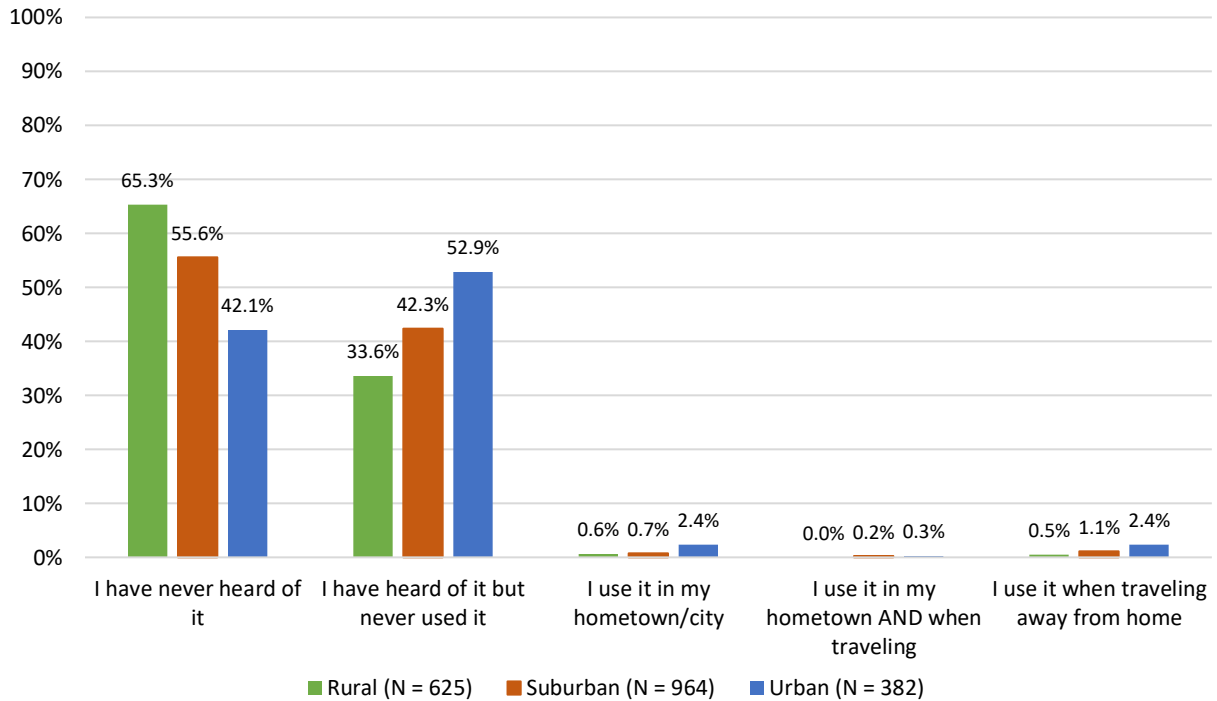


**Figure 20. Awareness and use of bikesharing by neighborhood type (total N = 1971, unweighted dataset)**

Among the respondents that have not used the service in their hometown, the residents of the San Francisco Bay Area reported the highest perceived availability of bikesharing (54%), while 58% of respondents from Northern California and the Central Valley do not believe that bikesharing is available in their region.
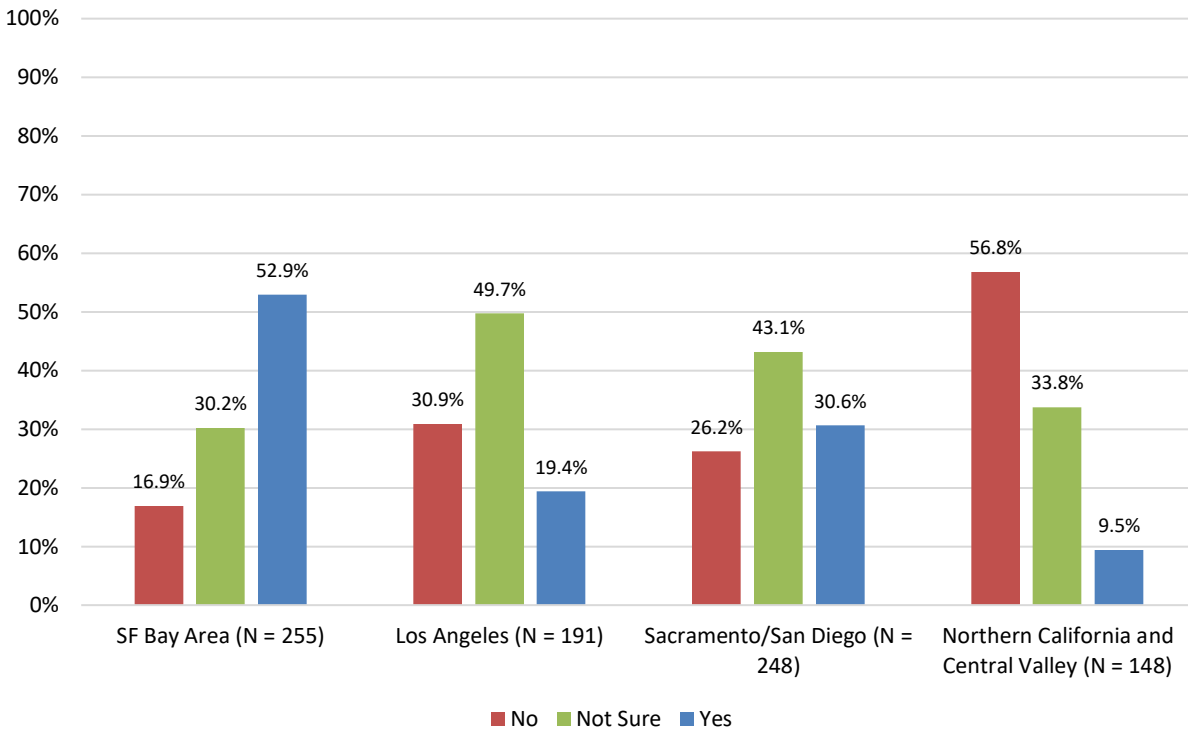


**Figure 21. Perceived availability of bikesharing by region (N = 842, unweighted dataset)**

A similar pattern is found by viewing responses by neighborhood type. Fifty percent of rural residents believe that bikesharing is not available in their area, compared to only 19% of urban residents.
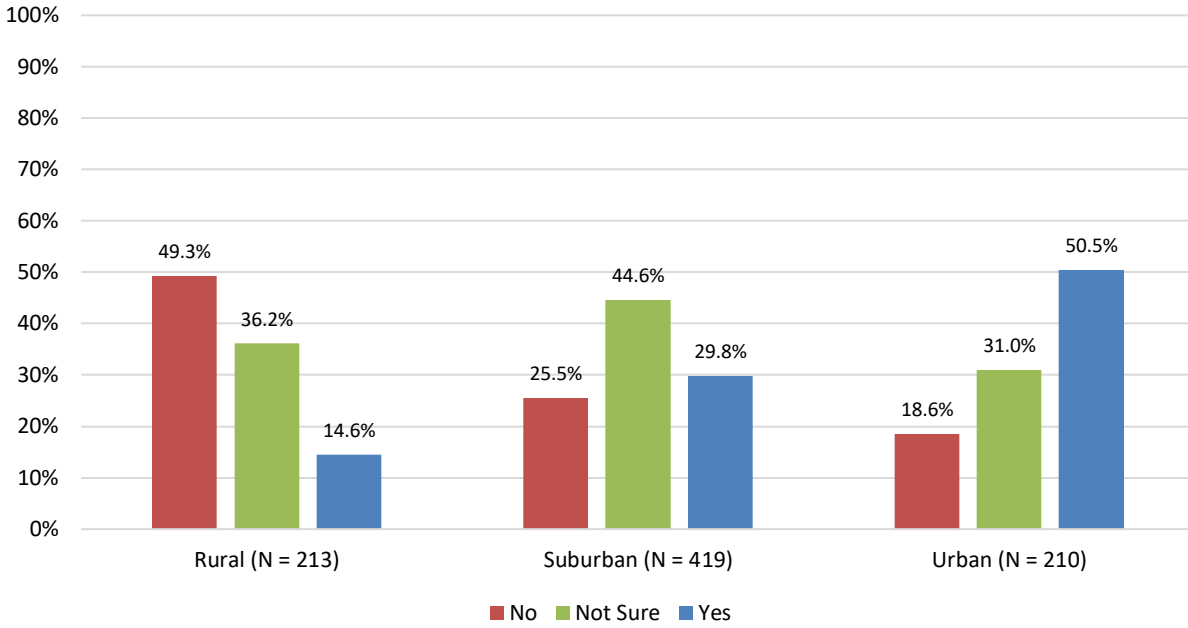
**Figure 22. Perceived availability of bikesharing by neighborhood type (N = 842, unweighted dataset)**

Few respondents in our study reported using bikesharing more frequently than 1-3 times a month, and no respondents reported using it 5 or more times a week.

## Adoption of ridehailing

Various factors may influence the adoption of on-demand ride services, such as individual and household socio-demographic characteristics, or the characteristics of a trip. However, most of the existing studies on this subject are descriptive and did not empirically test the impact of potential factors on the adoption of Uber or Lyft. In a recent paper written by the members of this research team (Alemi et al. 2017a), we explored the impact of personal attitudes and preferences, lifestyle, the built environment, and other individual characteristics on the use of on-demand ride services. We estimated two binary logit models of the adoption of on-demand ride services using various explanatory variables while controlling for typical demographic variables. The first model includes three groups of variables, controlling for socio-demographics, individual lifestyles, and built environment characteristics. The second model is a modified version of the first one, with the additional inclusion of individual attitudes among the explanatory variables. In this way, we test the impact of several factors that observers have identified as having a potential role as motivators for the use of on-demand ride services, and we investigate the circumstances under which individuals are more likely to use this type of service.

Figure 23 shows the distribution of users and non-users of such services by age group (millennials vs. members of the preceding Generation X). As shown in this figure, larger shares of millennials have adopted on-demand ride services (28.3%) compared to the older cohort (18.8%). To create the dependent variable for the model estimation, we grouped all individuals who reported having used such services in their hometown, away from home, or in both locations, and classified them as "users". Those who have heard about these services but have not used them yet and those who reported that they have not heard about these services were classified as "non-users".

We divided these explanatory variables into four main groups. The first group includes socio-demographic variables: age (a categorical variable representing *younger millennials,* between the age of 18 and 24 years old, *older millennials,* ages 25 to 34, *younger generation Xers,* between the age of 35 and 41 years old, and *older generation Xers,* ages 42 to 50); household income (with the range *$0-40K* of annual household income classified as low income, *$40-100K* as medium income, and *$100K or more* as high income); a dummy variable for the presence of children in the household; employment and student status; a dummy variable for non-Hispanic origin ethnicity; and the highest attained educational level (we defined individuals with a bachelor's degree or more as highly-educated individuals).

The second group of explanatory variables tests for the effect of the built environment, including the geographic region where the respondent lives and the self-reported neighborhood type. Controlling for the impact of the characteristics of the built environment on the adoption of on-demand ride services is important, as these services are not equally available across all California regions and all neighborhood types. To capture spatial heterogeneity and to test the impact of other built environment variables such as land use mix,

network connectivity, population density, and regional accessibility on the adoption of on-demand ride services, we geocoded the respondents' home locations and integrated the dataset with additional data extracted from the U.S. Environmental Protection Agency (EPA) Smart Location Dataset.
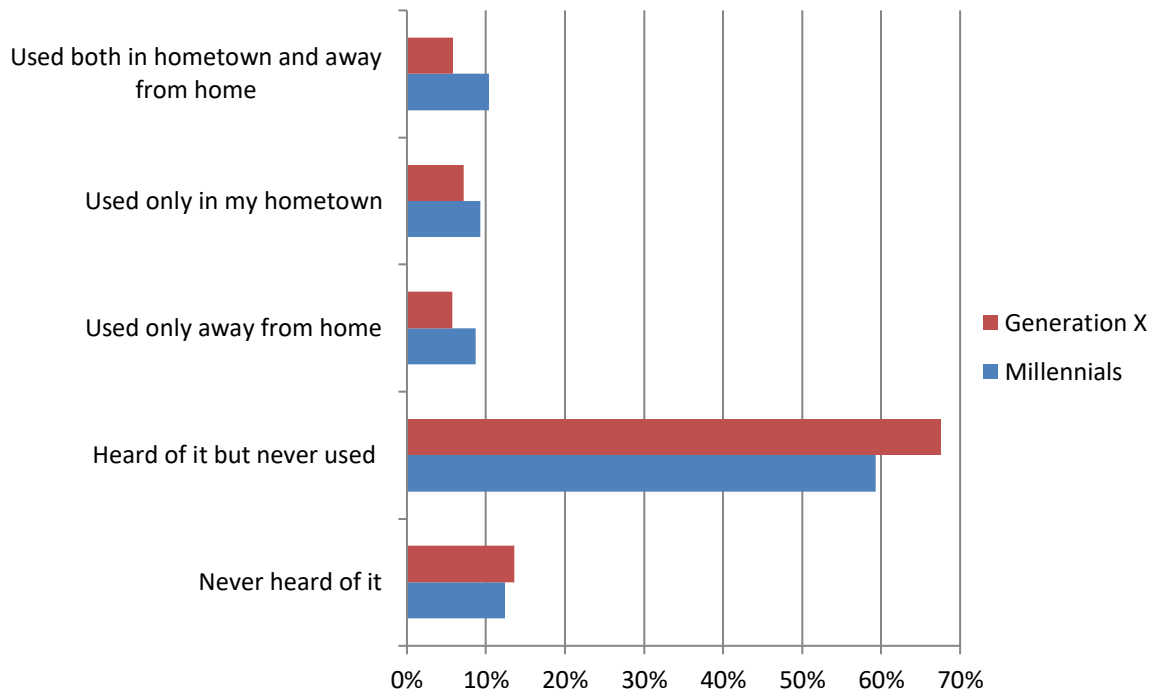


**Figure 23. Awareness and use of Uber and Lyft by age group (N$_{Millennials}$=1073, N$_{Gen X}$ = 888)**

A third group of variables controls for lifestyles with respect to individuals' propensity to use social media, ICT and other technological applications (in general, or to access transportation-related services), as well as the frequency of long-distance travel by purpose (business vs. leisure/personal) and by mode (e.g., car, plane, intercity bus and train). The literature has discussed some of these variables in the context of non-transportation sharing economy services (e.g., their relationships with the use of the peer-to-peer lodging services provided by Airbnb). For example, those who are more familiar with the use of technology more often search (or share) information online, and those who are more active on Facebook or other forms of online social media are also more inclined to adopt sharing economy services (Latitude 2010). We hypothesize that these individuals are also more likely to use shared mobility services.

The fourth group includes the attitudinal variables. As discussed earlier, we developed two models: the first model only accounts for the first three groups of variables, while the second also includes individual attitudes among the explanatory variables. Testing the impacts of individual attitudes on the adoption of technological transportation services such as those provided by Uber and Lyft is an important addition that was possible using the information

available in this dataset, whereas attitudinal variables are not commonly available in other datasets available for travel behavior research (such as those collected with national and most regional household travel surveys). In this second model, we included standardized Bartlett factor scores computed from the original attitudinal variables with a factor analysis, as described above. Among the 17 factors that were extracted, the *Technology Embracing*, *Variety Seeking* and *Pro-Environmental Policies* factors had significant effects on the adoption of shared mobility services and were included in the final model.

About half of the users of on-demand ride services are between the age of 25 and 34 years old (i.e., older Millennials), with Bachelor's degree or higher, whereas in the other two groups the shares of older millennials and those with high levels of education are significantly lower. This is also true with respect to technology adoption: users of on-demand ride services are frequent users of technology (e.g., they shop online and use transportation-related smartphone applications), while those who have heard about on-demand ride services but never used them, or those who have not heard about these services, do not use technology as frequently. The average scores of all three attitudinal factors among the users of on-demand ride services are positive and higher than the average among the two groups of non-users, reflecting more positive attitudes toward technology adoption, variety in life and pro-environmental policies among users.

In other model specifications, not reported here, we included an additional group of explanatory variables measuring the self-reported expected changes in individual travel behavior, such as the expected changes in the use of various transportation modes during the next three years, and the propensity to sell or replace one or more household vehicle(s). However, we excluded these variables from the final models, even though they had statistically significant coefficients, because they are likely endogenous and would therefore bias the coefficient estimates. For example, as discussed earlier in the literature review, recent Reuters/Ipsos opinion poll shows that about 10% of the users of on-demand ride services plan to dispose of their vehicles and turn to on-demand ride services as their primary means of travel (Henderson 2017), which supports the supposition that the decision to sell a household vehicle in the medium-term future could well be an effect rather than a cause of the adoption of shared-mobility services.

The result of the final models of the adoption of on-demand ride services (with and without attitudinal variables) are presented in Table 3. The first model, the model without attitudinal variables, is largely consistent with the results from previous studies based on descriptive statistics, and with our expectations. We found that the likelihood of adopting on-demand ride services is higher among well-educated individuals (individuals with bachelor's or higher degree level) and those who live in higher-income households compared to lower-educated individuals or those who live in lower/medium-income households. The same is true for older millennials, i.e., individuals between the age of 25 and 34 years old, consistent with other previous studies, including Rayle et al. (2014), where the authors showed that higher-educated individuals are more likely to use on-demand ride services. In our first model, being a student or worker

increases the likelihood of using on-demand ride services. However, the greatest increase in adoption of Uber/Lyft is among individuals who both work and study. The presence of children in the household reduces the probability of using on-demand ride services. However, this variable is not significant at the 90% significance level. In addition, we found that individuals of non-Hispanic origin are more inclined to adopt on-demand ride services.

The results of the first model show that individuals who live in urban neighborhoods are more likely to use on-demand ride services. This is not surprising, given that such services are more common (and easily accessible with shorter waiting time) in urban areas, compared to other neighborhood types. This is also true for those living in the major California metropolitan areas, such as San Diego, the San Francisco Bay Area, Sacramento or Greater Los Angeles: Living in major metropolitan areas increases the likelihood of using on-demand ride services (compared to the California Central Valley, Northern California, and the rest of the state, i.e., the regions where on-demand ride services are not as ubiquitous as in metro areas). Land use mix and regional auto accessibility measures also have significant impacts on the use of on-demand ride services. We found that the probability of adopting on-demand ride services increases as those land use mix and regional auto accessibility increase.

Not surprisingly, the degree of familiarity with modern technologies and their adoption in daily life is associated with the adoption of on-demand ride services. Individuals who perform more online shopping activities (including e-shopping, and purchasing/ reserving tickets and lodging through online services), and who use their smartphone more frequently regarding their daily travel (e.g., they navigate in real time more often), are more likely to use on-demand ride services. The same is also true for individuals who reported that they have already used other emerging transportation services such as carsharing, dynamic carpooling, and bikesharing in the past. Further, we found frequent long-distance travelers are more likely to use on-demand ride services. In particular, we found higher adoption rate among the individuals who make a higher share of long distance trips by plane.

The result of the second model, the model with attitudinal variables, was consistent with the result of our first model. To test for the impact of individual attitudes and preferences on the adoption of on-demand ride services, we incorporate factor scores as explanatory variables in the second model. Inclusion of attitudinal variables as factor score had only a small impact on the coefficients and statistical significance of the variables included in the first model, which indicates that the attitudinal variables are not highly correlated with the other variables in the model, i.e., that they are adding mostly independent explanatory power.

The result of the model with attitudinal variables showed that the rate of adoption of on-demand ride services is significantly higher among individuals with more positive factor scores on attitudes toward technology embracing, pro-environmental policies, and seeking variety in life. Interestingly, none of the other attitudes that we tested, including factors measuring attitudes toward (1) *car use and ownership* (e.g., "car as a tool" and "must own a car"); (2) *multitasking while commuting*; and (3) *mode choice* were significant.

**Table 3. Estimation results for binary logit model of the adoption of ridehailing (N=1818)**

| Variable | Model Without Attitudinal Variables | | Model With Attitudinal Variables | |
|---|---|---|---|---|
| | Estimates (P-values) | Robust Std. Error | Estimates (P-values) | Robust Std. Error |
| **Intercept** | -6.08 *(0.00)* | 0.41 | -5.77 *(0.00)* | 0.42 |
| ***Age*** | | | | |
| Younger Millennials | 0.81 *(0.00)* | 0.26 | 0.66 *(0.01)* | 0.27 |
| Older Millennials | 1.07 *(0.00)* | 0.19 | 1.00 *(0.00)* | 0.20 |
| Younger Gen X | 0.62 *(0.01)* | 0.22 | 0.53 *(0.02)* | 0.22 |
| ***Region*** | | | | |
| San Francisco Bay Area | 0.61 *(0.01)* | 0.23 | 0.59 *(0.01)* | 0.22 |
| San Diego | 0.98 *(0.00)* | 0.24 | 0.99 *(0.00)* | 0.24 |
| Greater Los Angeles | 0.89 *(0.00)* | 0.23 | 0.88 *(0.00)* | 0.23 |
| Sacramento | 0.67 *(0.01)* | 0.27 | 0.68 *(0.01)* | 0.27 |
| ***Presence of Children in the Household*** | | | | |
| Household with Kid(s) | -0.23 *(0.11)* | 0.14 | -0.26 *(0.07)* | 0.15 |
| ***Self-Reported Neighborhood Type*** | | | | |
| Urban | 0.53 *(0.00)* | 0.14 | 0.50 *(0.00)* | 0.15 |
| ***Household Income and Education Interaction*** | | | | |
| High Income Household and Highly Educated Individual | 0.94 *(0.00)* | 0.21 | 0.86 *(0.00)* | 0.21 |
| High Income Household and Low Educated Individual | 0.59 *(0.02)* | 0.26 | 0.54 *(0.04)* | 0.26 |
| Low/Medium Income Household and Highly Educated Individuals | 0.66 *(0.00)* | 0.17 | 0.70 *(0.00)* | 0.17 |
| ***Ethnicity*** | | | | |
| Hispanic Origin | -0.38 *(0.02)* | 0.16 | -0.43 *(0.01)* | 0.15 |
| ***Student and Employment Status*** | | | | |
| Work and Study | 0.93 *(0.00)* | 0.26 | 0.78 *(0.00)* | 0.26 |
| Work only | 0.48 *(0.02)* | 0.20 | 0.40 *(0.05)* | 0.20 |
| Study only | 0.55 *(0.07)* | 0.30 | 0.47 *(0.13)* | 0.31 |
| ***Use of Online Shopping*** | | | | |
| Higher/Medium Frequency | 0.48 *(0.00)* | 0.15 | 0.39 *(0.01)* | 0.15 |
| ***Use of Smartphone in Relation to Transportation (Navigating on Real-time)*** | | | | |
| Frequent users | 0.75 *(0.00)* | 0.15 | 0.57 *(0.00)* | 0.15 |
| ***Use of Taxi Services*** | | | | |
| Have used taxi services before | 1.12 *(0.00)* | 0.14 | 1.06 *(0.00)* | 0.14 |
| ***Use of Other Emerging Transportation Services (including carsharing, bikesharing, etc.)*** | | | | |
| Have used other shared-mobility services before | 1.15 *(0.00)* | 0.19 | 1.10 *(0.00)* | 0.20 |
| ***Land Use Mix*** | | | | |
| *8-Tier Employment Entropy* | 0.61 *(0.02)* | 0.25 | 0.63 *(0.01)* | 0.26 |
| ***Regional Accessibility*** | | | | |
| *Regional Centrality by Auto* | 1.09 *(0.00)* | 0.33 | 1.05 *(0.00)* | 0.34 |

| Variable | Model Without Attitudinal Variables | | Model With Attitudinal Variables | |
|---|---|---|---|---|
| | Estimates (P-values) | Robust Std. Error | Estimates (P-values) | Robust Std. Error |
| *Long Distance Travel* | | | | |
| Share of total long-distance trips by air | 0.93 *(0.00)* | 0.22 | 0.91 *(0.00)* | 0.22 |
| *Individual Attitudes (Factor Scores)* | | | | |
| Variety Seeking | - | - | 0.23 *(0.00)* | 0.07 |
| Technology Embracing | - | - | 0.34 *(0.00)* | 0.07 |
| Pro-Environmental Policies | - | - | 0.17 *(0.01)* | 0.07 |
| **Model Log Likelihood (AIC)** | -725.24 (1498.5) | | -709.44 (1472.9) | |
| $\bar{\rho}^2_{constant-based}$ | 0.26 | | 0.27 | |
| $\bar{\rho}^2_{equally\ likely-based}$ | 0.41 | | 0.42 | |

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

The inclusion of the attitudinal variables also slightly improves the goodness of fit of the model and reduces the magnitude of the estimated coefficients for the age group-related variables. This is a sign that some of the apparent impacts of age and generation on the adoption of on-demand ride services are more correctly explained by the personal attitudes of the individuals. As these attitudes are strongly correlated with age, when not controlling for attitudes, the effects of individual attitudes are attributed to the age group variables (thus, one could speculate that their effect would be simply attributed to the young age of ridehailing users, in studies that do not control for individual attitudes). Further, as individual attitudes are not perfectly correlated with age, it is desirable to distinguish the separate roles of age and attitude, as only the second model is able to do. In addition, the inclusion of the attitudinal variables diminishes the impact of technology adoption variables (including online shopping and the use of smartphones in relation to transportation). This confirms how technology savviness can be explained by technology-related attitudinal factors (and how the "true" impact of technology-embracing attitudes is attributed to the adoption of technology options per se in studies that do not control for individual attitudes). Similar results, with the same signs and comparable magnitude of the estimated coefficients, were obtained when estimating the equivalent models with the weighted dataset.

> **Key Findings 1: Adoption of Uber/Lyft**
>
> To investigate the factors that affect the adoption of ridehailing, we estimate several models that help assess the role of individual characteristics and residential location in affecting these choices. The results of a binary logit adoption model of Uber/Lyft show that:
> - Higher-educated older millennials (between 25 and 34, in 2015) are more likely to use ridehailing than other groups.
> - Greater land-use mix and more central urban locations are associated with higher adoption of Uber and Lyft.
> - Higher adoption is observed among individuals who make a large number of long-distance trips, and in particular those who travel more frequently by plane.
> - The degree of familiarity with ICT and other technology-enabled transportation services positively affects the adoption of Uber/Lyft.
> - Those who have previously used taxi and carsharing more likely use ridehailing.
> - The rate of adoption is significantly higher among individuals with stronger *technology-embracing*, *pro-environment*, and *variety-seeking* attitudes.

## Latent-class adoption model of ridehailing

To better understand the factors affecting the adoption of on-demand ride services while controlling for the heterogeneity behind the individual's decision, we expanded our previous analysis presented in the previous section through the estimation of a latent class choice model. We employed a latent class choice model to identify the factors affecting the adoption of on-demand ride services while controlling for variation in individuals' lifestyles and taste heterogeneity. We expect personal lifestyles as a higher-level orientation impacts all of an individual's decisions and choices. In addition, the development of classifications by lifestyle orientation could facilitate the forecasting of the adoption of on-demand ride services.

The impact of lifestyle on travel choices is irrefutable. Salomon and Ben-Akiva (1983) quantified the impact of lifestyles on travel behavior for the first time. In their study, the authors defined the three major life decisions as: (1) the formation of the household; (2) participation in the labor force; and (3) orientation toward leisure. Since then, a wide range of studies has quantified the impact of individuals' lifestyles on different components of travel behavior. Although the literature is converging on a formal definition of lifestyle as either a typology of behavior or latent factors motivating behavioral patterns, there is no consensus, yet, on the methods that can be employed to measure individuals' lifestyles. In the study by Van Acker (2015), the author illustrated three major approaches that have been used to measure lifestyles. The first approach is known as the *socioeconomic and demographic lifestyle* approach, where various objective socioeconomic and demographic characteristics as well as stage of life are used to characterize individual or household lifestyles. In the second approach,

researchers characterized lifestyles based on attitudes toward various topics (most importantly attitudes toward family, work and leisure), personality traits and related motives. This approach is known as the *sociographic* approach. Van Acker described the third approach, the *mechanistic lifestyle* approach, as a method which focuses on individual behavioral patterns. In this study, we characterize individual lifestyles based on their socioeconomic and demographic attributes, using Ganzeboom's three-dimensional indicators (1988, as cited in Van Acker et al. 2010), which measure an individual's economic, cultural and stage in life dimensions.

In our recent paper (Alemi et al. 2017b), we jointly estimate adoption of on-demand ride services and stochastically segment individuals based on their socioeconomic and demographic attributes (using Ganzeboom's three dimensional indicators), such that those who put similar weight on the various factors influencing their decision regarding the use of on-demand ride services are grouped together. This method is knowns as latent class choice models, which captures both unobserved and observed heterogeneity by grouping decision makers into discrete classes that are not immediately identifiable from the data (Walker and Ben-Akiva 2002) without requiring an analyst to make prior unwarranted assumptions about the distributional parameters or number of clusters (Greene and Hensher 2003).

Latent class choice models comprise two models: (1) the class membership model and (2) the class-specific choice model. We defined our latent classes such that represent the variations in individual lifestyles, whereas the factors affecting the adoption of on-demand ride services are tested in the class-specific choice models of the adoption of Uber/Lyft. We defined the probability of adoption or non-adoption based on a binary logit formulation. To create our binary dependent variable, we grouped all individuals who reported that they have used on-demand ride services regardless of the location where they used these services and classified them as "users". Those who have heard about these services but have not used them yet were classified as "non-users". We excluded from the modeling portion of this study the individuals who reported that they have not heard about Uber and Lyft, since this group of individuals is the smallest one in size, and we expected to see the individuals in this group to behave differently once they become familiar with the service.

Similar to our adoption model discussed in the previous section, after careful review of the existing literature on the adoption and use of shared-mobility services, sharing economy, and lifestyles, we divided the explanatory variables available in the California Millennial Dataset into the four main categories: (1) Socio-demographic variables; (2) Built environmental variables; (3) Technology adoption and the use of social media; and (4) Long distance travel and number of vehicles in the households. For more detailed information about the model estimation and variable selection see Alemi et al. (2017b).

We selected the 3-class model as the best model, based on model's goodness of fit, interpretability of classes and classification errors. As indicated in Table 4, the results of the class-membership model showed that individuals in Class 1 (37% of total respondents) tend to be more affluent and are usually *dependent* millennials (e.g., young adults that still live with

their family of origin) or older members of Generation X. In most cases, individuals in this class live in households with children below 18 years old. Members of this class also tend to only work or only study, which is consistent with other attributes such as age distribution and household composition of this class. *Independent* millennials (i.e., those not living with their parents) are grouped mainly in Class 2 (33% of total respondents): members of this class are usually not married and tend to live in households without kids. This class has the highest number of individuals who both work and study at the same time. Individuals with the lowest education level and who are the least affluent are more likely to belong to Class 3 (30% of total respondents). This class has the highest share of younger members of the Generation X and has a large share of individuals who do not work or study. Examining the residential neighborhood parameters, we found that both Class 1 and Class 2 include large shares of urban and suburban dwellers, while Class 3 has a high proportion of rural dwellers.

We looked at the distribution of other inactive covariates (i.e., variables not included in the model), to better understand the class membership profiles. Figure 24 presents the distribution of gender, ethnicity, region and ratio of the number of vehicles per drivers in the household for the three latent classes. As indicated in Figure 24, differences among classes with respect to the distribution of male and female respondents and the ratio of the numbers of vehicles per drivers in the household are not significant.

**Table 4. Results of the class membership model (N=1,526)**

| | Class 2 (33%) Coefficients (t-ratio) | Class 3 (30%) Coefficients (t-ratio) | Distribution across Classes | | |
| --- | --- | --- | --- | --- | --- |
| | | | Class 1 | Class 2 | Class 3 |
| **Age and Stage of Life** | | | | | |
| Younger Dependent Millennials | -29.62 (-4.83) | -27.79 (-5.73) | 15% | 1% | 4% |
| Younger Independent Millennials | 10.24 (3.94) | 6.83 (1.54) | 1% | 14% | 12% |
| Older Dependent Millennials | -14.45 (-4.68) | -34.08 (-5.69) | 8% | 7% | 2% |
| Older Independent Millennials | 4.29 (3.18) | -4.31 (-2.05) | 22% | 56% | 20% |
| Younger Gen X | Reference Category | | 23% | 17% | 30% |
| Older Gen X | -12.3 (-4.89) | -5.26 (-2.87) | 32% | 4% | 32% |
| **Presence of Children in the Household** | | | | | |
| Household with Kid(s) | -14.42 (-3.86) | -13.19 (-5.52) | 72% | 25% | 49% |
| Household without Kid(s) | Reference Category | | 28% | 75% | 51% |
| **Marital Status** | | | | | |
| Married | -9.42 (-5.62) | -13.51 (-3.33) | 67% | 41% | 43% |
| Not Married | Reference Category | | 33% | 59% | 57% |
| **Household Income** | | | | | |
| Very Low | -6.61 (-2.15) | 10.52 (3.72) | 3% | 3% | 22% |
| Low | -6.13 (-3.8) | -6.24 (-1.08) | 19% | 16% | 18% |
| Medium | Reference Category | | 41% | 33% | 37% |
| High | 11.55 (3.63) | 8.26 (3.44) | 14% | 32% | 17% |
| Very High | 4.07 (2.34) | -1.05 (-0.36) | 23% | 16% | 6% |
| **Employment & Student Status** | | | | | |
| Works Only | Reference Category | | 64% | 64% | 46% |
| Studies Only | 3.34 (2.10) | -6.83 (-3.00) | 9% | 7% | 5% |
| Works and Studies | -2.91 (-2.40) | -25.74 (-6.34) | 13% | 17% | 1% |
| Does not Work nor Study | 4.36 (1.86) | 9.37 (6.20) | 14% | 12% | 47% |
| **Education** | | | | | |
| High Education | -4.11 (-2.06) | -15.35 (-6.04) | 63% | 64% | 15% |
| Lower Education | Reference Category | | 37% | 36% | 85% |
| **Neighborhood Type** | | | | | |
| Urban | Reference Category | | 32% | 23% | 6% |
| Suburban | 9.83 (5.00) | 13.7 (3.48) | 46% | 60% | 39% |
| Rural | 7.79 (3.15) | 23.54 (5.91) | 21% | 16% | 55% |
| **Constant** | 7.96 (3.22) | 10.3 (2.23) | | | |

*Note: Italicized coefficients and t-ratios are significant at 95% confidence interval level; Class 1 was used as the base class for the class segmentation*
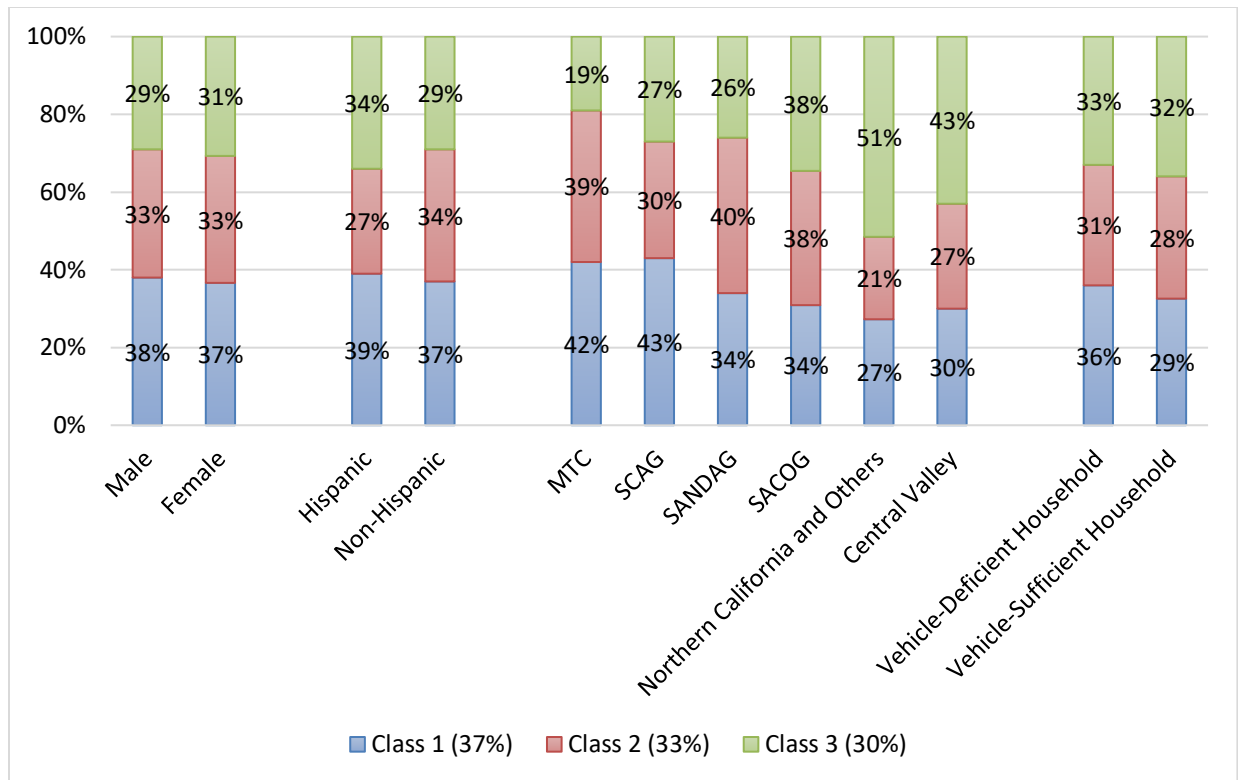
**Figure 24. Distribution of inactive covariates by classes (N=1,526, unweighted dataset)**

The share of Hispanic respondents is higher in Class 3 compared to the other two classes, and it is lowest in Class 2. Another noticeable pattern is the distribution of the members of each class by region of California. About half of the respondents from the California *Central Valley* and the *Northern California and Other* regions are members of Class 3.

The results of the class-specific adoption model showed that the adoption of on-demand ride services significantly varies across the classes. The members of Class 2, which largely comprises older independent and higher educated millennials, have the highest rate of adoption of on-demand ride services, with an adoption rate of 47%, meaning that 47% of the members of this class had used Uber/Lyft at the time of the survey. The second highest adoption rate (27%) belongs to the members of Class 1. The members of this class tend to live in more affluent households and are more likely to be younger dependent millennials or highly educated older members of Generation X. The lowest rate of adoption rate (only 5%) is associated with members of Class 3, i.e., lower educated individuals who predominantly live in lower income households and are more likely to neither work nor study.

Table 5 shows the parameter estimates of the class-specific adoption models. As shown in this table, we restricted a subset of model parameters to be equal across the three classes. The first two of these class-independent variables are the two dummy variables for the Northern and Southern California regions that control for differences in the accessibility and availability of on-

demand ride services (a measure of supply) across regions of California. The San Francisco Bay Area (MTC) and Sacramento region (SACOG), here grouped together in the "Northern regions," have been a popular test bed for different technology-enabled transportation options, including on-demand ride services.

In addition, these services have quickly become popular across the large metropolitan areas of the southern regions of California, including Los Angeles (SCAG) and San Diego (SANDAG). The likelihood that individuals will adopt these services in any of these more developed regions is expected to be higher than for residents of the remaining and more rural areas.

We also tested the use of region-specific adjustments for each of these regions, but the estimated coefficients were not statistically different between the MTC and SACOG regions, and between the SCAG and SANDAG regions, respectively. Further, when examining the class-dependent parameters and the corresponding Wald statistics, we found that the impacts of the use of carsharing and taxi services do not differ across classes in a statistically significant way. As a result, we included these two parameters as class-independent parameters. Similarly, across all classes, and without statistically significant differences across them, we found that individuals who reported that they have previously used taxi services or carsharing are more likely to adopt on-demand ride services. This finding was consistent with the results of the binary model that we previously estimated (Alemi et al., 2017a).

Class-dependent parameters show how the impacts of some variables vary across classes. Looking at the magnitude and direction of each class-specific coefficient, we found that the adoption of on-demand ride services increases as transportation-related use of smartphones (i.e., use of smartphone apps to determine the route and destination) and the number of business-related trips made by plane, train or intercity bus increase for the members of Class 1. The adoption of Uber/Lyft for the members of this class is also found to depend on the economic conditions of the household: the probability of adoption of on-demand ride services increases if the members of Class 1 live in households with annual income of $60,000[7] or higher. The use of smartphones was also found to be significantly (and positively) associated with the adoption of Uber/Lyft among the members of Class 1. In addition, the members of Class 1 are more likely to use on-demand ride services if they have made more long-distance trips for business purposes by plane, train and inner-city bus in the last 12 months. By comparison, the impact of long-distance business travel on the adoption of on-demand ride services is not significant among the members of Class 2 (nor among the members of Class 3), probably because the members of Class 2 use Uber/Lyft regardless of these occasional business-related circumstances (analogously, the members of Class 3 are not likely to use Uber/Lyft whether they travel long-distance for business or not).

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

**Table 5. Class-specific choice model estimation results**

| Variables | Class independent | | Class 1 | | Class 2 | | Class 3 | |
|---|---|---|---|---|---|---|---|---|
| | Coefficients | Robust t-statistics | Coefficients | Robust t-statistics | Coefficients | Robust t-statistics | Coefficients | Robust t-statistics |
| **Region** | | | | | | | | |
| Northern Region | 0.29 | 1.02 | | | | | | |
| Southern Region | 0.63 | **2.45** | | | | | | |
| **Use of Other Emerging Transportation Services** | | | | | | | | |
| Carsharing | 2.05 | **5.82** | | | | | | |
| **Use of Taxi** | 1.14 | **7.08** | | | | | | |
| Use Taxi before | | | | | | | | |
| **Use of Smartphones** | | | | | | | | |
| To Determine Destination and Route | | | 0.52 | **2.98** | 0.46 | **2.55** | 0.33 | 0.66 |
| **Built Environment** | | | | | | | | |
| Transit Performance index | | | 0.04 | 0.85 | 0.10 | **1.91** | 0.37 | **1.59** |
| Land Use Mix | | | *0.68* | 1.27 | *0.42* | 0.70 | *-4.79* | **-2.88** |
| **Long Distance Travel** | | | | | | | | |
| Frequency of Long Distance Business Trips by Non-car Modes (log-transformed) | | | 0.53 | **3.39** | 0.00 | 0.00 | 0.22 | 0.27 |
| Frequency of Long Distance Leisure Trips by Plane (log- transformed) | | | *-0.13* | -0.60 | *1.59* | **5.14** | *1.63* | **3.12** |
| **Household Income** | | | | | | | | |
| Household Income (60K+) | | | *0.51* | **1.81** | *-0.94* | **-3.00** | *0.01* | 0.02 |
| **Intercept** | | | *-3.43* | **-6.51** | *-2.41* | **-4.94** | *-4.76* | **-3.89** |

Note: Bold robust t-ratios are significant at 95% confidence interval level and italicized coefficients vary significantly across classes

The members of Class 2 tend to use on-demand ride services if they have traveled more for leisure purposes by plane (e.g., they use the service to get to/from an airport) in the last 12 months. The differences between the impacts of the frequency of long-distance trips for leisure purposes among the members of Class 1 and Class 2 may stem from the differences in household structures between the two classes. Members of Class 1 may ask other members of the household for a ride to/from the airport, while members of Class 2 (which most often include unmarried younger individuals) have fewer options to get a ride to/from the airport from another household member. Interestingly, the members of Class 2 are less likely to adopt on-demand ride services if their household earns more than the median household income in California (i.e., $60,000 or higher), showing the potential impact that household income may have on multimodality and the use of emerging transportation services. Specifically, for the members of this class, higher income is often associated with higher accessibility to vehicle ownership: independent millennials are more likely to live in zero- or low-vehicle-ownership households, but as income increases, the likelihood of the members of this group to have higher auto availability increases. In addition, the impact of household income on the use of on-demand ride services among the members of Class 2 can be an indication of transient conditions such as age, student and work status.

As indicated in Table 5, the adoption rate among the members of Class 3 is more likely to be impacted by the characteristics of the built environment than is the case for the members of the other classes. The adoption of on-demand ride services decreases as land-use mix increases. This could be associated with the lower average of the ratio of number of vehicles per household driver among the members of Class 3 and their average socio-economic status: due to lower vehicle availability per driver in the household and lower household income, the members of Class 3 may be more multimodal and rely on alternative modes (e.g., public transit) if they live in highly accessible areas and areas with higher quality of transit. Members of both Class 2 and Class 3 tend to adopt on-demand ride services if they live in neighborhoods with higher transit performance scores (i.e., served by better quality of public transit) but land-use mix does not have a significant effect for the members of Class 2. That said, the transit performance score measures the overall quality of transit as well as job accessibility by transit, which could be a proxy for other built environmental characteristics such as land use density, network density, regional centrality and walkability, due to the high correlations among many of these land use measures.

To better account for individuals' heterogeneity and taste variation with respect to the use of Uber/Lyft, we estimate a latent-class adoption model:

- Users of ridehailing can be grouped into three well-defined latent classes, based on their individual and household characteristics, lifestyles and stage in life.
- The highest adoption rate (47%) is observed among the members of the class that is largely composed of higher-educated independent millennials who live in more urban locations. The adoption rate in this class is higher for individuals that make more long-distance leisure trips and are more frequent users of ICT and smartphone apps.
- The second highest adoption rate (27%) is observed among the members of a class mainly composed of affluent older Gen Xers and dependent millennials living with their families. The adoption of ridehailing in this class is higher for individuals who make more long-distance trips for business purposes, have higher income and use ICT more often.
- The lowest adoption rate (5%) belongs to the members of the class with the highest share of rural dwellers and of individuals with low education and/or who live in low-income households. Land-use mix and transit accessibility play an important role in affecting the use of ridehailing among the members of this class.

## Frequency of use of ridehailing

This section expands our previous work by investigating the factors that affect the frequency of Uber and Lyft. To our knowledge, this is a first application of multivariate models to improve the understanding of the factors affecting both the adoption and frequency of use of on-demand ride services. Very few studies have investigated the factors affecting the frequency of the use of on-demand ride services. For example, in a recent study by the Pew Research Center (2016), authors found that out of the 15% of respondents in their sample who reported that they have used on-demand ride services (N=4,787), only 3% and 12% reported that they have used on-demand ride services on a daily and weekly basis, respectively. This research confirmed that younger adults tend to use on-demand ride services more frequently. In another study, Feigon et al. (2016) showed that the most frequent users of on-demand ride services live in middle-income households (annual incomes of $50 to 75K). Both studies showed that Uber/Lyft frequent users are more likely to live in households with lower-than-average numbers of vehicles per driver, and are more likely to rely more on other means of transportation, including public transit or active modes (Pew Research Center 2016; Feigon et al. 2016). However, the extent to which the adoption of on-demand ride services *causes* such changes is not clear. This leads to the second category of studies.

To investigate the factors that affect the frequency of use of on-demand ride services, we estimated an Ordered Probit model with Sample Selection (OPSS), while controlling for the separate process that influences the adoption of the services. Sample-selection models may be considered the most appropriate method for modeling the frequency of using on-demand ride services, because we only asked the frequency question from the individuals who have previously used on-demand ride services. The exclusion of individuals who have not adopted on-demand ride services (yet) would artificially inflate the coefficients associated with the exogenous variables included in a frequency model (in the direction of the effects of adoption), if there are common unobserved factors that affect both the adoption and frequency of use of on-demand ride services. We also estimated a Zero-Inflated Ordered Probit (ZIOP) model of the frequency of use of on-demand ride services. The rationale behind the use of this model is that due to the time frame of the survey, some cases currently classified as non-users are likely to adopt these services as their popularity and visibility increase. Those who have not used on-demand ride services yet *but will do so in the future* (similarly to those who have used Uber/Lyft but in the past) can be considered *zero-frequency users,* rather than *non-users*. More detailed information on the model estimation and explanatory variables used in our final models are contained in (Alemi et al. 2018a).

As discussed, the dependent variable of interest measures the frequency of use of on-demand ride services. Figure 25 presents the distribution of the adoption and frequency of use of these services. Millennials are more likely than the members of the older cohort to adopt on-demand ride services and tend to use these services more often.
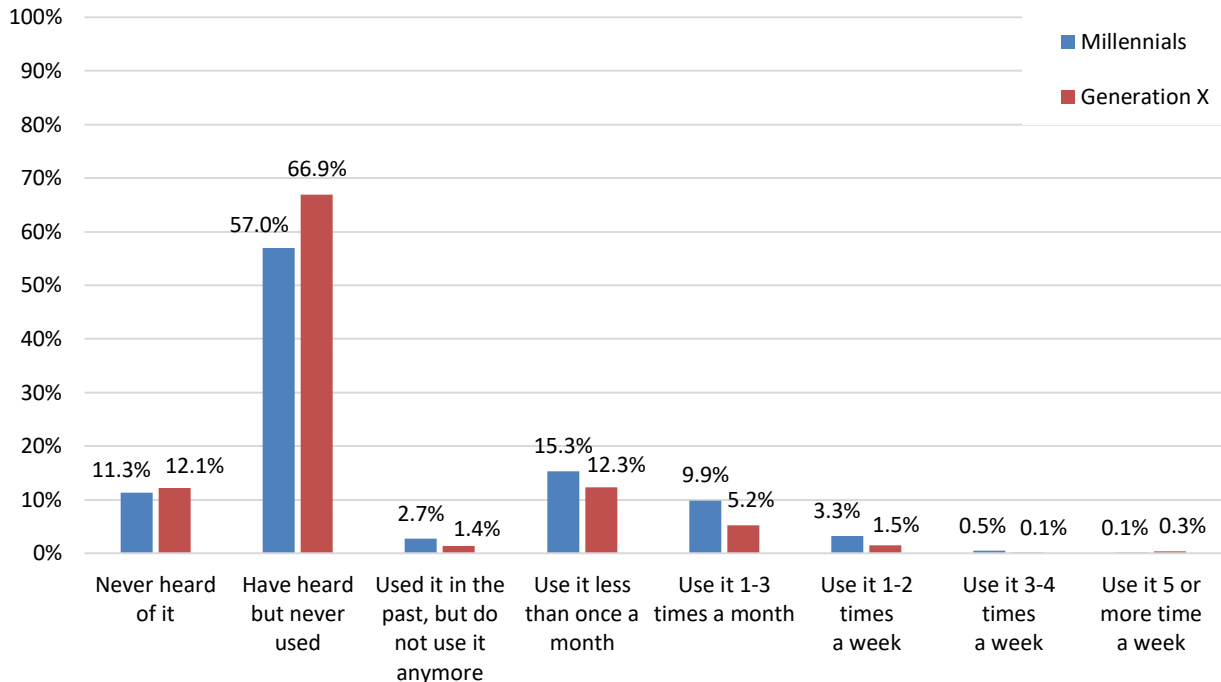


**Figure 25. Adoption and frequency of use of Uber and Lyft by age group ($N_{Millennials}$=1043, $N_{Gen\,X}$ = 916)**

We created the dependent variable used in the model estimation, grouping all individuals who used on-demand ride services at least once a month, including those who used it "5 or more times a week", "3-4 times a week", "1-2 times a week" and "1-3 times a month". We also grouped those who "have heard but never used on-demand ride services" and those who "used the services in the past but do not use it anymore" into the category of non-users. Those who have not heard about these services were excluded from the rest of the analysis, since we did not measure their perceptions of factors that limit their use of on-demand ride services, the variables that were used in our final model specifications. Figure 26 and Table 6 present the distribution of the dependent variable that we used for the estimation of the frequency models by age group, and other key explanatory variables, respectively. As indicated in Figure 26, millennials tend to use on-demand ride services more frequently: About 17% and 15% of millennials reported using on-demand ride services respectively less than once a month or at least once a month, while the usage frequency of these services was lower among Gen Xers.
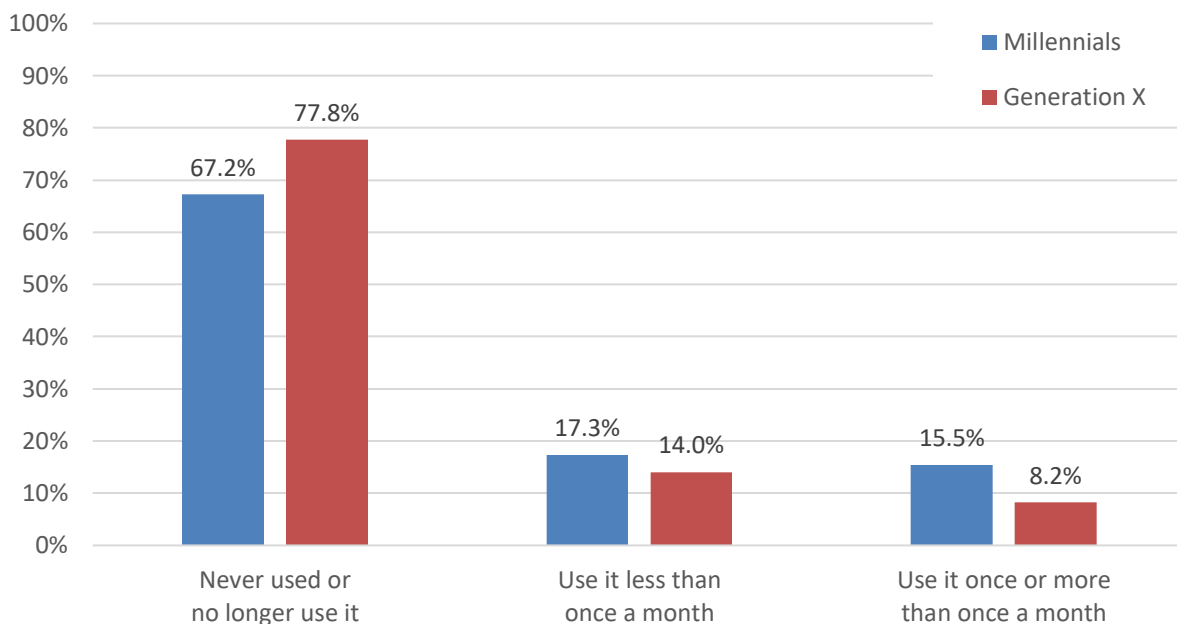


**Figure 26. Frequency of use of Uber/Lyft by age group (N$_{Millennials}$=925, N$_{Gen X}$ = 805)**

We divided the key explanatory variables used in our final models into five main groups: (1) Sociodemographic variables; (2) Built environmental variables; (3) Technology adoption and the use of social media; (4) Travel-related choices; and (5) General attitudes and specific perceptions of attributes of on-demand ride services.

Table 6 presents the result of both OPSS and ZIOP models of the frequency of use of on-demand ride services. As indicated in this table, the estimated coefficients from the OPSS model are largely consistent with those from the ZIOP model, with some exceptions that are

discussed in the following paragraphs. The result of both models showed that none of the sociodemographic variables influences the frequency of use of on-demand ride services, whereas these variables significantly impact the adoption process. Among different sociodemographic variables, we found that independent millennials and better-educated individuals (i.e., individuals with Bachelor's degrees or higher) are more likely to use on-demand ride services, largely consistent with findings from previous studies (Rayle et al. 2014; Alemi et al. under review). This is also true for individuals who live in a household without any children. We expect that the coarse frequency categories might have masked the potential impact that sociodemographics might have on the frequency of use on-demand ride services.

Both models confirmed that an increase in land use mix is associated with a decrease in the frequency of use of on-demand ride services, possibly due to the use of other means of transportation (mainly active modes) facilitated by greater proximity to destinations within walking and biking distances. Another important built environment factor that impacts frequency is land use density: increasing activity density (number of jobs and housing units per acre) leads to an increase in the frequency of use of on-demand ride services. To make sure that the difference in the impact of land use density and land use mix is not an artifact of our models, we checked the correlation between these two variables and also estimated models with and without either of these two variables. The very low correlation between land use mix and activity density (= 0.101) and the negligible changes in the estimated coefficients confirm that these two built environment attributes impact on-demand ride services in opposite directions. The results of both the selection and inflation models also showed that living in areas with higher transit performance scores increases the likelihood of adopting on-demand ride services.

The variable related to use of smartphone in connection with transportation is also significant in both selection/inflation and frequency models. Individuals who used a smartphone in connection with their transportation more frequently (e.g., to navigate in real time, learn how to get to new places, identify possible destinations and check traffic to plan route or departure time) are more likely to adopt the services and use them with higher frequency. We checked the equality of the impact of this factor in the frequency and selection/inflation models, and found that the magnitude of this factor does not significantly vary between the models. We also tested the impact of the use of other emerging transportation services on the frequency of on-demand ride services and find that individuals who have used fleet-based carsharing systems (e.g., Zipcar) are more likely to have adopted on-demand ride services. Further, the results of the OPSS model show that there is a negative association between the use of fleet-based carsharing and the frequency of use of on-demand ride services, confirming the competition among the new shared-mobility services, a controversial topic that has been gaining attention in the popular media.

We also find that frequent taxi users (i.e., individuals who reported that they use taxi services at least once a month) are more likely to also use Uber/Lyft frequently. Further, the results of both the OPSS and ZIOP models indicate that respondents who reported higher shares of long-

distance leisure trips made by plane are more likely to adopt the services and to use them more frequently. Both models also confirm that individuals who live in zero-vehicle households tend to use Uber/Lyft more frequently. We also observed a similar pattern among individuals who reported that they prefer to use (have) their own vehicles: the preference to have their own vehicles decreases the likelihood of both adopting and using on-demand ride services frequently in both the OPSS and ZIOP models.

In addition to the impacts of attitudinal variables such as the *Variety Seeking*, *Pro-Environmental Policy* and *Technology Embracing* factors, we found that individuals with higher levels of agreement with the statement capturing their willingness to pay to reduce their travel time (i.e., higher perceived value of time) tend to use Uber/Lyft more frequently. This variable was only significant in the ZIOP model; similarly, the variable had statistically significant effects in early versions of the OPSS model, but the magnitude of the impact of this variable diminished after including other variables in our OPSS, and the variable did not have statistically significant effects in the final model. Accordingly, we excluded this variable from the final OPSS model specification.

**Table 6. Estimation results of sample selection and zero-inflated ordered probit models (N=1610)**

| | Ordered Probit with Sample Selection | | | | Zero-inflated Ordered Probit Model | | | |
| | Selection Model | | Frequency Model | | Inflation Model | | Frequency Model | |
| **Variables** | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error |
|---|---|---|---|---|---|---|---|---|
| ***Age and Stage of Life*** | | | | | | | | |
| Younger Dependent Millennials | 0.22 (0.25) | 0.19 | -- | | 0.28 (0.20) | 0.22 | -- | |
| Younger Independent Millennials | 0.50 *(0.00)* | 0.17 | -- | | 0.59 *(0.00)* | 0.18 | -- | |
| Older Dependent Millennials | 0.32 (0.10) | 0.19 | -- | | 0.29 (0.18) | 0.22 | -- | |
| Older Independent Millennials | 0.56 *(0.00)* | 0.12 | -- | | 0.59 *(0.00)* | 0.13 | -- | |
| Younger Gen X | 0.21 (0.10) | 0.13 | -- | | 0.23 (0.10) | 0.14 | -- | |
| ***Education*** | | | | | | | | |
| High (Bachelor's degree or higher) | 0.26 *(0.00)* | 0.09 | -- | | 0.29 *(0.00)* | 0.10 | -- | |
| ***Presence of Children in the Household*** | | | | | | | | |
| Household with Kid(s) | -0.28 *(0.00)* | 0.09 | -- | | -0.22 *(0.02)* | 0.10 | -- | |
| ***Region*** | | | | | | | | |
| San Francisco Bay Area | 0.08 (0.59) | 0.15 | -- | | 0.12 (0.46) | 0.17 | -- | |
| Sacramento | 0.20 (0.21) | 0.16 | -- | | 0.18 (0.33) | 0.18 | -- | |

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| Variables | Ordered Probit with Sample Selection | | | | Zero-inflated Ordered Probit Model | | | |
|---|---|---|---|---|---|---|---|---|
| | Selection Model | | Frequency Model | | Inflation Model | | Frequency Model | |
| | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error |
| Greater Los Angeles | 0.22 (0.12) | 0.14 | -- | | 0.29 (0.06) | 0.16 | -- | |
| San Diego | 0.38 (0.01) | 0.14 | -- | | 0.44 (0.01) | 0.16 | -- | |
| *Land Use Mix* | | | | | | | | |
| 8-Tier Employment Entropy | -- | | -0.45 (0.03) | 0.21 | -- | | -0.59 (0.06) | 0.31 |
| *Land Use Density* | | | | | | | | |
| Standardized Activity density | -- | | 0.18 (0.00) | 0.06 | -- | | 0.22 (0.00) | 0.07 |
| *Transit Quality and Access* | | | | | | | | |
| Transit Performance Index | 0.05 (0.00) | 0.02 | -- | | 0.04 (0.02) | 0.02 | -- | |
| *Use of Smartphone* | | | | | | | | |
| Apps to Determine Destination and Route | 0.21 (0.00) | 0.05 | 0.18 (0.03) | 0.08 | 0.20 (0.00) | 0.06 | 0.36 (0.00) | 0.11 |
| *Use of Other Emerging Transportation Services* | | | | | | | | |
| Used Fleet-based Carsharing | 1.01 (0.00) | 0.00 | -0.4 (0.02) | 0.17 | 0.90 (0.00) | 0.20 | -- | |
| *Frequency of Using Taxi Services* | | | | | | | | |
| Used Less than Once a Month | 0.35 (0.00) | 0.09 | -- | | 0.50 (0.00) | 0.10 | -- | |
| Used at Least Once a Month | 0.51 (0.00) | 0.17 | 1.09 (0.00) | 0.21 | 0.77 (0.00) | 0.18 | 1.09 (0.00) | 0.22 |
| *Frequency of Long Distance Travel* | | | | | | | | |
| Frequency of Non-car Long Distance Business Travel | 0.13 (0.04) | 0.06 | -- | | -- | | -- | |
| Frequency of Long Distance Leisure Travel by Plane | 0.43 (0.00) | 0.07 | 0.17 (0.09) | 0.10 | 0.50 (0.00) | 0.08 | 0.32 (0.00) | 0.11 |
| *Vehicles Per Household Driver* | | | | | | | | |
| Zero-Vehicle Household | -- | | 0.89 (0.01) | 0.32 | -- | | 0.69 (0.06) | 0.37 |
| *Attitudes and Perceptions* | | | | | | | | |
| Variety Seeking | 0.13 (0.01) | 0.05 | -- | | 0.11 (0.03) | 0.05 | -- | |
| Technology Embracing | 0.21 (0.00) | 0.05 | -- | | 0.22 (0.00) | 0.05 | -- | |
| Pro-Environmental Policies | 0.12 (0.00) | 0.04 | -- | | 0.12 (0.01) | 0.05 | -- | |
| Pay to Reduce Travel Time | -- | | -- | | -- | | 0.18 (0.02) | 0.08 |

| Variables | Ordered Probit with Sample Selection | | | | Zero-inflated Ordered Probit Model | | | |
|---|---|---|---|---|---|---|---|---|
| | Selection Model | | Frequency Model | | Inflation Model | | Frequency Model | |
| | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error | Estimates (P-values) | Std. Error |
| Perceived Uber/Lyft Cost- & Time-related Limitations | -0.12 (0.02) | 0.05 | -- | | -0.12 (0.03) | 0.06 | -- | |
| Preference to Use Non-car Mode | -0.17 (0.00) | 0.05 | -- | | -0.19 (0.00) | 0.05 | -- | |
| Knowledge about the Services | -0.33 (0.00) | 0.05 | -- | | -0.36 (0.00) | 0.06 | -- | |
| Preference to Use Own Vehicle | -0.13 (0.00) | 0.04 | -0.12 (0.04) | 0.06 | -0.11 (0.05) | 0.05 | -0.32 (0.00) | 0.08 |
| *Constant* | -2.09 (0.00) | 0.18 | -- | | -2.26 (0.00) | 0.21 | -- | |
| *Threshold 0 → 1* | -- | | -1.7 (0.00) | 0.19 | -- | | -1.65 (0.00) | 0.57 |
| *Threshold 1 → 2* | -- | | 0.04 (0.88) | 0.23 | -- | | 0.72 (0.00) | 0.23 |
| **Correlation Parameter (ρ)** | -0.51 *(0.00)* | | | | -- | | | |
| **Final Model Loglikelihood** | -958.24 | | | | -787.86 | | | |
| **AIC [BIC]** | 1990.50 [2189.71] | | | | 1645.72 [1834.16] | | | |

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

The magnitude and significance of the correlation term ρ in the Sample Selection model indicates that there is a very substantial and significant negative correlation between the unobserved factors affecting adoption and frequency of use of on-demand ride services. We confirmed the significance of the correlation term through performing a likelihood ratio test of independence (H$_0$: ρ=0). The significant negative correlation term reveals that some individual traits or other attributes that are not controlled in the final OPSS model impact Uber/Lyft's adoption and frequency in opposite directions (similar to the impact of fleet-based carsharing, an observed variable that positively impacts the adoption of on-demand ride services and negatively impacts the frequency of use of these services).

Currently we are working on expanding and addressing some of the limitations of these analyses (a) through the inclusion of a correlation term in the ZIOP model, and (b) by incorporating preference heterogeneity and taste variation (as latent classes) into the zero-inflated ordered model. This will allow us respectively to control for potential correlation among unobserved factors in the zero-inflated models and to better account for differences in individual decision processes among different groups of individuals. In the next section of this report, we briefly discussed the factors limits or encourage the use of on-demand ride services, based on our recent paper (Alemi et al., 2018b).

**Key Findings 3: Frequency of use of Uber/Lyft**

We estimate an ordered probit model with sample selection and a zero-inflated probit ordered model to explore the impacts of various explanatory variables on the frequency of use of Uber/Lyft:

- About 17% and 15% of millennials used ridehailing less than once a month and at least once a month, respectively, while these shares decrease to 14% and 8%, respectively, for the member of Generation X.
- Sociodemographics are good predictors of adoption but not so much of frequency.
- Individuals who live in a zero-vehicle household are more likely to use Uber/Lyft with higher frequency.
- Frequent long-distance travelers (by plane, in particular) use Uber/Lyft more often.
- Land-use mix and activity density (i.e., population and job density) impact the frequency of use of ridehailing.
- Individuals who frequently use smartphone apps to determine destination and route choice are more likely to both adopt ridehailing and use it more often.
- The frequency of use decreases for the individuals who report having strong preference to use (have) their own vehicle.
- There is competition among shared mobility services: carsharing users are more likely to also use ridehailing, but frequent users of carsharing tend to use Uber/Lyft less frequently.

## Limitations to the Use of Ridehailing

As discussed earlier, the availability and popularity of on-demand ride services are quickly growing: according to new statistics released on November 2016, Uber and Lyft operate in more 500 and 100 U.S. cities, respectively, with pooled services available only in selected large cities and metropolitan areas, such as San Francisco, San Diego, and Seattle.[8] As the popularity and availability of these services increase the proportion of total trips made with these services is expected to increase, potentially causing large effects on future travel patterns. A recent study of on-demand ride services in the City of San Francisco showed that the share of total trips made with Uber and Lyft reaches to 15% (170,000 trips per day) of all trips inside the city of San Francisco on a typical weekday (SFCTA 2017). This is equivalent to 20% of total vehicle miles traveled (VMT) inside the city of San Francisco, and 6.5% of total VMT including both intra- and inter-city trips. The role of Uber and Lyft will likely become even more central as society transitions towards a future dominated by autonomous vehicles and *mobility as a service*. Thus, planners and policy makers have a strong interest in improving the understanding of the potential impacts that the use of on-demand ride services has on other components of travel behavior, and the factors that increase or limits the use of these services.

In this section of the report, we explored the factors that limits or encourage the adoption and frequency of the use of on-demand ride services, and the potential impacts these services have on the other components of travel behavior including vehicle ownership and the use of other means of transportation. To do so, we first used the information reported by respondents on their familiarity with and use of various types of emerging shared mobility services in their home town or while traveling. For those who reported that they have used any shared mobility services, we asked about the frequency of the use of them. In addition to the familiarity, adoption and frequency of use of emerging services, we asked users of on-demand ride services to rate the importance of different factors that affect their use of the services, how their adoption impacted their use of other means of transportation, and what they would have done if these services had not been available on their last trip they made by Uber or Lyft. We also asked user and those who reported that are familiar with on-demand ride services but have not used these services yet to evaluate the important of the factors that may limit their use of on-demand ride services.

We asked respondents who used on-demand ride services to evaluate the importance of a series of factors affecting their last trip made by Uber/Lyft, including the ease of payment, cost, ability to split fare, shorter wait time, fastest way to get to destination, ease to hail a service, drivers (e.g., friendless or ability to speak the respondents' language), comfort/safety, reliability of services, difficulties with parking when driving their own car, the need to avoid drinking and driving, as well as the unavailability (limited availability) of other modes including public transit services, taxicabs, and personal vehicles. This question helped us to expand our knowledge about factors affecting the use and frequency of use of Uber/Lyft as perceived by the users of

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[8] https://uberexpansion.com/lyft-vs-uber-side-by-side-comparison/ (last accessed on March 14, 2018)

these services, beyond what we have discussed so far in previous sections. Figure 27 summarizes the factors that affect the use of Uber/Lyft. The users of on-demand ride services more often report to be affected by the quality of ridehailing services – the ones that have been neglected by taxi service providers– rather than by attributes of the other modes of transportation, with two exceptions: parking and drink and driving. More than 80% of respondents reported that parking, including both difficulty in finding a parking space and cost of parking, is a moderately to extremely important reason affecting their decision to use Uber/Lyft. Further, about 60% of the respondents reported that they used on-demand ride services to avoid driving under an influence.
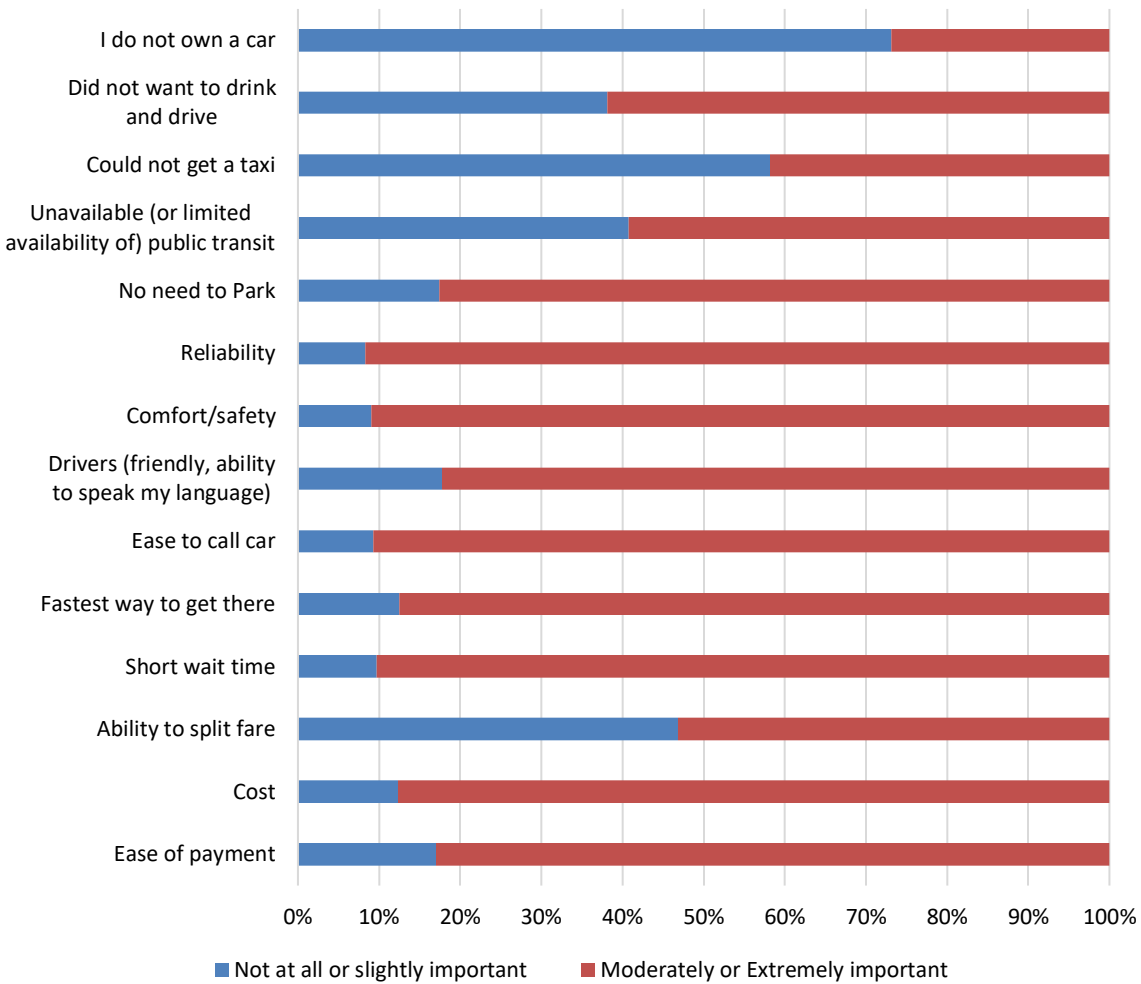


**Figure 27. Importance of factors affecting individual's last trip made by Uber/Lyft (N=529, weighted sample)**

Among the various characteristics of on-demand ride services, respondents put their highest emphasis on the shorter wait time, cost, ease to call a car, and drivers (including both friendliness and ability to communicate with riders) as the characteristics that seem most

relevant. Further, we looked at the distribution of the importance of these factors among frequent users (i.e., those who used on-demand ride services at least once a month) and non-frequent users (i.e., those who used these services less than once a month).

**Table 7. Factors limiting or preventing the use of Uber/Lyft (N$_{Users}$=529, N$_{Non-users}$ =1207, weighted sample)**

| | Users | Non-users |
|---|---|---|
| Lack of knowledge of/familiarity with the service | | |
| Availability of the service in the area where I need it | | |
| Availability of the service at the time I need it | | |
| Difficulty of payment | | |
| Cost | | |
| Waiting time when I need to use the service | | |
| Concern about drivers | | |
| Concern about comfort/Safety | | |
| Prefer to have/use my own vehicle | | |
| Concern about the legality of the service | | |

Legend: ■ Strongly limits  ■ Somewhat limits  ■ It does not limit

The largest discrepancy was observed in the importance of the availability of personal vehicle: 35% of frequent users of on-demand ride services reported that unavailability of personal vehicle was an important factor that affect their decision to use Uber/Lyft, while only 17% of non-frequent users evaluated this factor as an important contributing one, indicating some association between vehicle ownership (availability) and the frequency of use of on-demand ride services. Among other factors, we found that the importance of ease of payment, the ability to split the fare and the unavailability of public transit are perceived rather differently between frequent and non-frequent users of the services.

We also asked both users of on-demand ride services and those who reported that they have heard about the service but not used it yet to evaluate the importance of the factors limiting or preventing their use of these services. The results are reported in Table 7. Among the limiting factors, both users and non-users ranked their preference to use their own vehicle as the most important one: About 38% of users and 56% of non-users evaluated the preference to use their own vehicle as the most important factors limiting their use of on-demand ride services. Further, about 20% of users and 27% of non-users reported that the cost of service strongly affects their use of on-demand ride services. These two limiting factors suggest a promising future in potential increase in use of on-demand ride services, if these shared services become more ubiquitous and are offered at lower cost points. Further, more than 1/3 of non-users reported that they are strongly concerned about the drivers and service's comfort/safety. Comparing frequent and non-frequent Uber/Lyft users, we found that only 28.8% of frequent users reported the preference to use (have) my own vehicle as a limiting factor to their use of on-demand ride services, whereas the importance of this factor increased to 44.7% among the non-frequent users of on-demand ride services.

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**Key Findings 4: Limitations to the use of Uber/Lyft**

Participants were asked to evaluate what factors limit their use of ridehailing, and the importance of several service attributes in affecting their use of Uber/Lyft:

- The preference to use one's own vehicle was reported as the most important factor limiting the use of ridehailing.
- The concerns about comfort/safety and the cost of the service are respectively the second and third most reported factors limiting the use of Uber/Lyft.
- Users report that the short waiting time and the easiness to call a car are the most important reasons for using the service.
- More than 80% of respondents reported that parking (including both the difficulty of finding a parking space and the cost of parking) was a moderately important to extremely important reason affecting their decision to use Uber/Lyft.
- About 60% of the respondents reported that they have used ridehailing to avoid drinking and driving.

## Adoption of Ridehailing and Use of Other Travel Modes

Research on the impacts that ridehailing services have on other components of travel behavior is still limited, largely because of the lack of longitudinal data or robust analytical approaches that capture the causal relationships among the use of on-demand ride services and other components of travel behavior. Most studies in this area, to date, are based on the analysis of descriptive statistics and self-reported behavioral changes and/or rely on the analysis of convenience samples. Accordingly, it is often difficult to extrapolate the findings from these studies and apply them to the entire population. Additional difficulties associated with these studies include the eventual maturation of the impacts of ridehailing use over time, and the heterogeneity in behavioral changes across different segments of the population.

Recent studies indicate that the impact of shared-mobility services on other means of transportation may vary based on the type of services available, the local context, and the characteristics of the users (Taylor et al. 2015; Circella et al. 2016). For example, 40% of TNC users in San Francisco reported that they reduced their driving due to the adoption of on-demand ride services (Rayle et al. 2014). Further, depending on local circumstances, travelers may use on-demand ride services as a substitute for or as a complement to the use of public transit. For example, a survey of 4,500 users of shared-mobility services revealed that frequent users of shared mobility tend to use public transit more often and are more multimodal than non-users. Some of this relationship may be due to the correlation of both behaviors with third-party variables such as low car ownership or living in more accessible locations. A study carried out by the Shared-Use Mobility Center (2016) found that the majority of trips made with ridehailing services occurs between 10 pm and 4 am, when public transportation either runs very infrequently or does not run at all. On the other extreme of the spectrum, public transit may lose its riders as the share of ridehailing services increases: a study of seven large U.S. metro areas showed that these services tend to substitute 6% and 3% of the trips that would have been otherwise made by bus and light rail, respectively (Clewlow and Mishra 2017).

To explore the potential impacts that on-demand ride services may have on the use of other transportation modes, we looked at Uber/Lyft users' responses to two questions: (1) one question asked how the most recent Uber/Lyft trip affected the use of other means of transportation; and (2) the second question asked how the respondent would have made that trip (if at all), if these services had not been available. We discussed the distribution of the potential impacts that these services may have on the other means by age groups in Alemi et al. (2017a). The results showed that the majority of both millennials and Gen Xers reduced their amount of driving because of the use of Uber/Lyft.
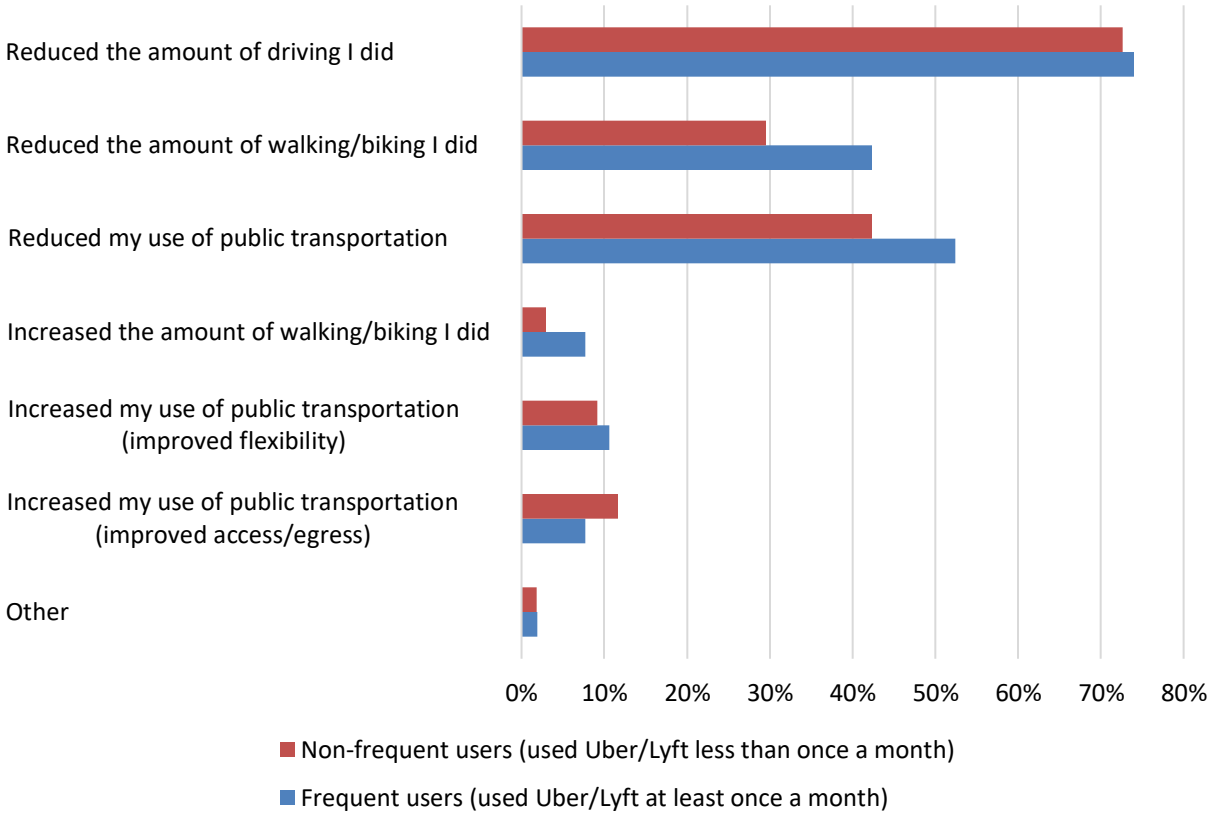
**Figure 28. The impact of Uber/Lyft on the use of other means of transportation by frequent and non-frequent Uber/Lyft users (N$_{Frequent\ users}$=208, N$_{Non\text{-}Frequent\ users}$ =274, weighted dataset, multiple answers allowed for each respondent)**

In this report, we focus on the impacts on the use of other modes, by types of travelers (frequent vs. non-frequent users). Figure 28 presents the effect of the most recent trip made by Uber/Lyft on the use of other means of transportation among those who use Uber/Lyft at least once a month (frequent users) and those that do so less than once a month (non-frequent users). The use of on-demand ride services tends to reduce the amount of driving (alone) among both frequent and non-frequent Uber/Lyft users. Somewhat worrisome, the use of these services also substitutes for some trips that would have otherwise been made by transit or active modes. This is truer for frequent users of on-demand ride services, those who live in zero-/lower vehicle household and those who are more multimodal.

Figure 29 shows how frequent and non-frequent Uber/Lyft users would have traveled if Uber or Lyft had not been available for the last trip made with these services. This second question provided additional options to respondents, including "would have gotten a ride from someone", "would have taken a taxi" and "would have used a van or shuttle service". In the first question, these options were not offered explicitly, so it is reasonable to assume that respondents might have selected "reduce the amount of driving" as a proxy for some of these options, too.
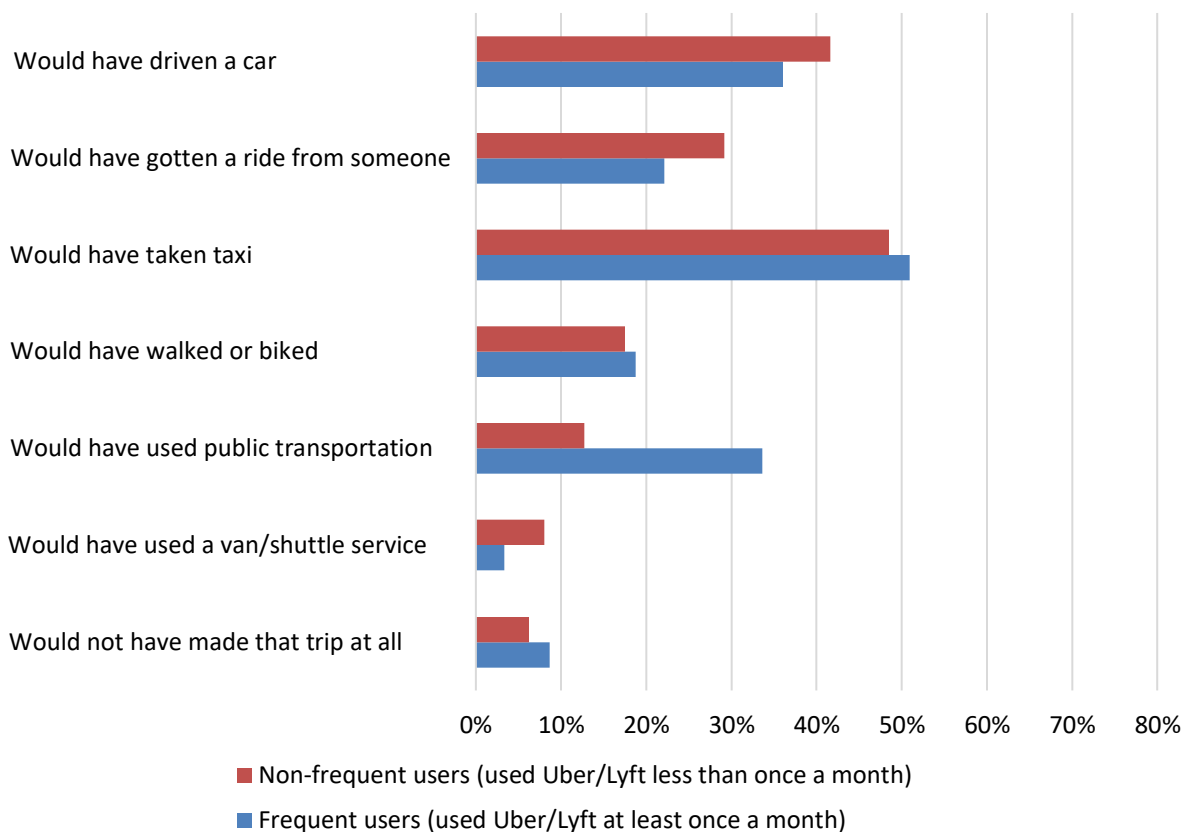
**Figure 29. How users would have traveled in the absence of Uber/Lyft among frequent and non-frequent Uber/Lyft Users (N_Frequent users=208, N_Non-Frequent users =274, weighted dataset, multiple answers allowed for each respondent)**

The majority of frequent and non-frequent users report that they would have hailed a taxi if Uber and Lyft were not available. This confirms the presence of competition between these services and taxicabs. About 42% and 29% of non-frequent users reported that they would have driven a car or have gotten a ride from someone else, respectively. These shares reduced to 37% and 22%, respectively, among the frequent users of on-demand ride services, confirming different car-dependencies and availability among frequent and non-frequent users. Again, something worrisome, a larger proportion of frequent Uber/Lyft users would have used public transportation or active modes in the absence of Uber/Lyft.

We also compared the availability of personal vehicles (as a ratio of number of vehicle in the household to number of household member with a driver's license) among users and non-users and found that frequent users of on-demand ride services are more likely to live in zero-/lower vehicle households compared to non-frequent users or those who have not used on-demand ride services. In addition, we found that the likelihood of being willing to reduce the number of households' vehicles is higher among frequent users of on-demand ride services, consistent with a recent opinion poll conducted by Reuters/Ipsos (Henderson 2017).

Nevertheless, there is no study that confirms the causal relationships among the use of on-demand ride services and other components of travel behavior, including use of private vehicles and public transportation, multimodal travel, vehicle ownership and vehicle miles traveled. Specifically, it is not yet clear the extent to which the adoption of shared-mobility services causes an increase in public transportation use (for example), as opposed to both of those conditions being caused by other variables (such as residential location, age/stage in lifecycle, and vehicle ownership), as also suggested by the estimation of a bivariate order probit model of the use of Uber/Lyft and of public transportation (Circella et al., 2017c). Further, large uncertainty exists on how these relationships vary among different sociodemographic groups and in different geographic contexts.

To be able to investigate the impact of these services on the other modes and vehicle ownership a more robust analytical approach is required. This would allow testing different causality structures and what directions should be considered. In the next stage of the research, the availability of longitudinal data will allow us to investigate the relationships among the adoption of ridehailing services (and of pooled ridehailing services such as UberPOOL and Lyft Line) and other components of travel behavior and vehicle ownership, over time. This analysis will allow disentangling potential causality relationships between the adoption of these services and other observed changes in individual and household travel-related choices. In the following sections, we first present the result of our in-depth analysis of self-reported behavioral changes caused by the use of ridehailing services, and then discuss how the use of ridehailing impacts the use of public transportation using respondents' revealed behavior.

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### Key Findings 5: Impacts of Uber/Lyft on the use of other travel modes

We analyze the self-reported information on the effects that the last trip made by Uber and Lyft had on other travel modes:

- A large majority of the respondents (including both frequent and non-frequent users) reported that the use of Uber/Lyft reduced their use of a personal car.
- The use of ridehailing substitutes for some trips that would have otherwise been made by transit or active modes. This substitution effect is stronger among frequent ridehailing users, individuals that live in zero-/low-vehicle households and multimodal travelers.
- The majority of non-frequent users reports that they would have driven a car, gotten a ride from someone else, or taken a taxi if Uber/Lyft were not available.
- Somewhat concerning from the perspective of environmental sustainability and the promotion of active lifestyles, a larger proportion of millennials reduced their amount of walking and biking as the result of the use of ridehailing.
- Further, frequent users of ridehailing more often report that they are considering reducing the number of household vehicles than the rest of respondents in the sample.

## Latent-class analysis of impacts of ridehailing on other modes

To better understand how the use of ridehailing affects the use of other means of transportation, we conducted a latent-class analysis of the self-reported behavioral changes in the use of other means of transportation that can be attributed to the use of ridehailing. We expect that the latent-class analysis of self-reported behavioral changes can provide more meaningful and scientifically interesting results against the noisy background compared to other existing approaches. We performed the latent-class analysis only on the self-reported behavioral changes, and did not include any covariates. Further, we assumed that the observed dependent variables are independent and their residuals are distributed independently. Figure 30 summarizes the attributes of each latent classes and shows how the use of ridehailing affect the use of other transportation mode.
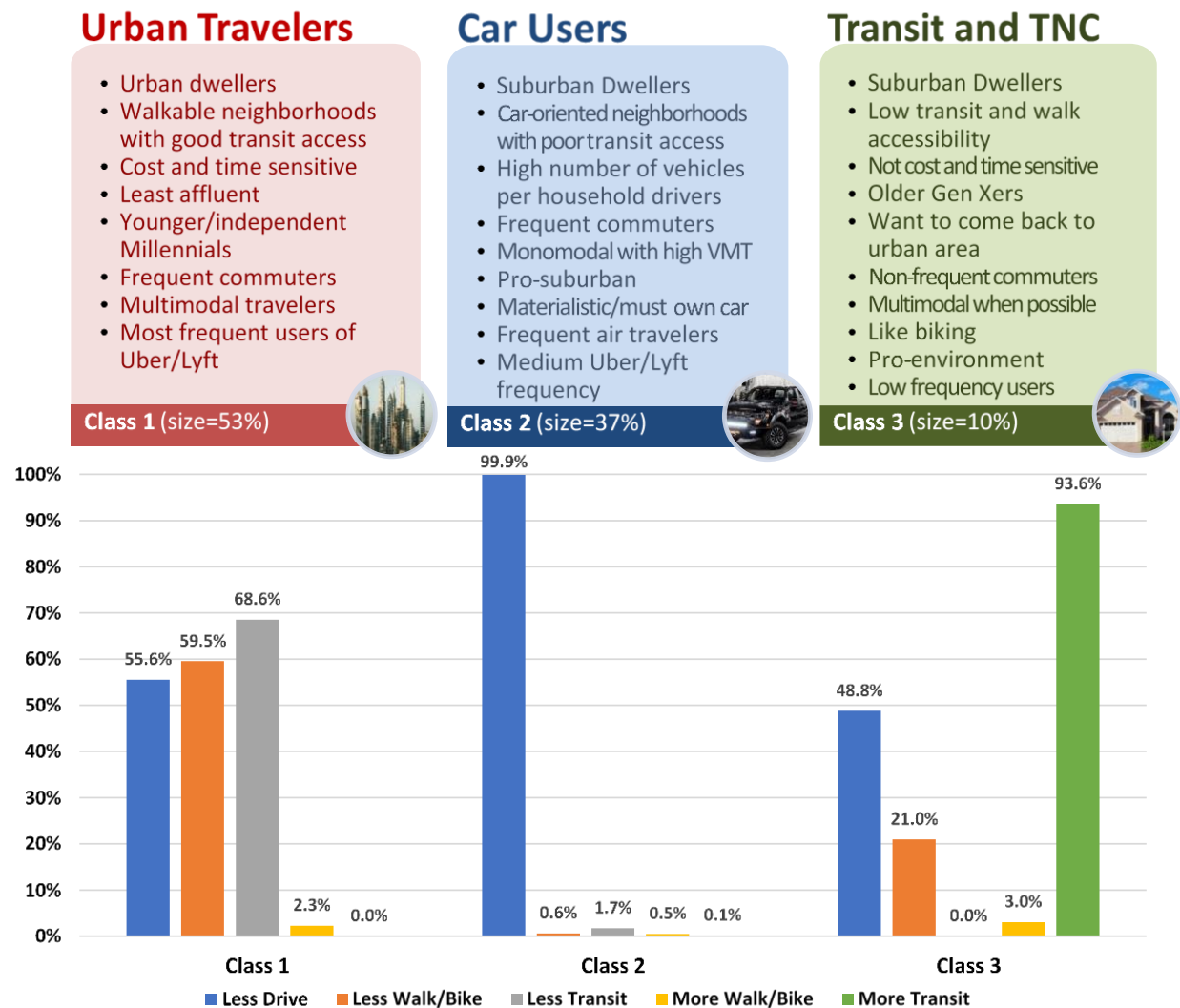


**Figure 30. Impacts of the use of ridehailing on other travel modes for three latent classes of ridehailing users (N=482, unweighted dataset, multiple answers allowed for each respondent)**

As indicated in this figure, three rather well-defined latent classes are identified in the latent-class analysis.

- *Class 1:* This class accounts for about 53% of the Uber/Lyft users in our dataset, the members of which are more likely to live in urban neighborhoods characterized by higher public transit access/connectivity and higher walkability. This class largely composes of younger adults and independent millennials, and cost- and time-sensitive individuals who travel frequently using a combination of multimodal alternatives. The members of this class tend to use ridehailing more frequently, compared to the members of the other two classes. As shown in Figure 30, the use of ridehailing reduces the use of personal vehicles, public transit and walking/biking. We expect that providing ridehailing at lower cost (e.g., through promoting the pooling services) brings the largest impact on the members of this class, who have the highest cost and time sensitivity. In the next stage of our analysis, we plan to expand our analysis through incorporating key confounders (e.g., sociodemographics and characteristics of the built environment) to better understand the impacts of ridehailing on different means of transportation.

- *Class 2:* This class accounts for 37% of the ridehailing users in our sample and comprises suburban dwellers who live in neighborhoods with very low transit access/connectivity. The members of this class live in households with the highest ratio of vehicles per household drivers, drive for most trip purposes (i.e., they are monomodal) and, as a result, have the highest Vehicle Miles Driven (VMD) in the sample. Consistent with their travel behavior, the members of this class report the strongest positive attitudes toward car ownership, use of personal vehicles, and living in suburban neighborhoods. Uber/Lyft users in this class tend to use ridehailing with medium frequency, for reasons such as traveling to/from airports (the members of this class travel more often by plane than other users in the sample). The use of Uber/Lyft replaces the use of personal vehicles among the members of this class. Although the members of this class are not very cost sensitive, we expect that any changes in the cost of driving and the characteristics of the built environment in the residential and school/work place would affect their use of ridehailing and ultimately the potential impacts that these services have on the use of other transportation modes.

- *Class 3:* Class 3 is the smallest class (accounts for only 10% of Uber/Lyft users in the sample), largely composed of older members of Generation X and dependent millennials who live with their families in suburban neighborhoods. The members of this class have the lowest sensitivity to cost and time factors, bike/walk or use public transit when possible (the members of this class are more attracted by the use of public transit but often live in areas that are poorly served by public transportation). The members of this class like biking and reported the strongest positive pro-environmental attitudes. Interestingly, this group of Uber/Lyft users often report they would like to move to more urban neighborhoods, which could be an indicator of their stage in life (e.g., empty

nesters) or other personal/household attributes. The average frequency of use of ridehailing of the members of this class is the lowest in the entire sample. However, the use of ridehailing has the most desirable outcome in terms of sustainable transportation among these travelers: the use of ridehailing increases the use of public transportation among the member of this class, through providing an access mode to connect to/from public transportation terminals or stations. Future policies that focus on the integration of ridehailing services with public transit should focus on expanding the basis of users that can have such environmentally-beneficial effects associated with the use of ridehailing.

This is an on-going research, and we plan to expand our analysis in a number of ways, including (1) incorporating the impact of other confounders (e.g., key sociodemographics and built environmental variables) and (2) allowing for local dependencies (i.e., allowing the residual of dependent variable to co-vary/be jointly distributed).

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**Key Findings 6: Latent-class analysis of impacts of Uber/Lyft on other modes**

We employed a latent-class analysis approach to classify users based on the self-reported behavioral changes associated with the use of ridehailing. Three well-defined latent classes were identified:

- The largest class (53% of users in our sample, including most frequent users) is mainly composed of independent millennials who live in walkable neighborhoods that are highly accessible by transit and who are multimodal travelers. Ridehailing has mixed effects on these users, contributing to reducing the use of personal cars, transit and active modes.
- Ridehailing substitutes for the use of a personal vehicle among the member of the second largest class (37% of users) that is composed of affluent suburban dwellers with positive attitudes towards car ownership and use, and high VMT.
- The use of Uber/Lyft increases the use of public transit (e.g., providing access to transit stations) among a group of predominantly suburban dwellers who live in less accessible areas but try to be multimodal when possible and have pro-environmental attitudes. This group only includes 10% of users, who use ridehailing occasionally.

## Ridehailing and public transportation use

To better understand the potential impact of the use of Uber/Lyft on other components of travel behavior while controlling for the effects of sociodemographics and other confounding factors, we tested several model structures, including (a) a public transportation frequency model (which includes the use of Lyft/Uber as an explanatory variable), (b) a seemingly unrelated bivariate probit model and (c) a bivariate recursive probit model of the frequency of use of Uber/Lyft and the frequency of use of public transit for non-commute purposes.

We find that public transportation frequency is largely determined by sociodemographics, built environment characteristics and the use of smartphone-based transportation apps. Frequent users of Uber and Lyft are more likely also to use public transportation frequently, though this might not entail a causality relationship. Rather, it might be the impact of other latent constructs or lifestyle orientation (e.g., mobility or modality style: some users might be more inclined to use both public transportation and Uber/Lyft frequently).

The three types of bivariate models that were estimated lead to somewhat similar results: we find that the frequency of use of Uber/Lyft and the frequency of use of public transit are significantly (and positively) correlated. This confirms that there are some unobserved factors that positively impact the frequency of use of both Uber/Lyft and public transportation. More investigation is required to better understand the true nature of this relationship (which cannot be fully explored through the analysis of cross-sectional data), and to identify the impacts of different lifestyles and mobility styles and the potential causality links between the use of Uber/Lyft and the use of public transportation.

For additional details on these model results, please refer to Tiedeman and Circella (2018), and Circella et al. (2017c).

## Conclusions and Policy Implications

This study provides initial insights into the factors that affect the adoption and frequency of use of shared mobility services, such as Uber/Lyft, carsharing and bikesharing. It helps planners and policy makers better understand how shared mobility services are transforming transportation, what factors respectively limit/encourage their use, and how their adoption affects the use of other modes of transportation.

Among other findings, the results from this study show that better-educated individuals who live in predominantly urban areas are more likely to use ridehailing services, consistent with what was suggested in previous studies based on descriptive statistics (Rayle et al. 2014, Taylor et al. 2015, Shared-Use Mobility Center 2016). We find that increased land-use mix and regional auto accessibility increase the likelihood of using ridehailing. Further, the adoption of on-demand ride services is higher among individuals who make more long-distance trips and those who travel more by plane.

We estimated a latent-class adoption model to control for variation in individuals' preferences and behaviors and group individuals based on similar observed behavioral patterns. We identified three classes of ridehailing adopters: a class largely composed of more highly educated, independent millennials with the highest adoption rate of Uber/Lyft. The second highest adoption rate is observed among the members of the class that is mainly composed of affluent individuals living with their families who are either dependent millennials or highly educated, older members of Generation X. The likelihood of using ridehailing increases with the number of long-distance airplane trips for the members of this class. Finally, the lowest adoption rate is observed among the least affluent individuals with the lowest level of education, who predominantly live in rural regions.

We find that built environment variables explain more variation in the frequency of using ridehailing than sociodemographic variables. Land-use mix and activity density contribute to respectively decreasing and increasing the frequency of use of on-demand ride services. Individuals who live in zero-vehicle households and those with higher shares of long-distance leisure trips made by plane are more likely to adopt these services and use them more often. Users of carsharing services are also more likely to adopt ridehailing. However, high-frequency carsharing users tend to use Uber/Lyft less frequently. Among various attitudes and perceptions, individuals with stronger preferences to own a personal vehicle are less likely to be frequent users of Uber/Lyft.

With respect to the factors that limit or encourage the adoption of these services, we find that the use of Uber/Lyft is highly affected by attributes of the service such as cost and average waiting time. Respondents report the "easy way to call a ride through the smartphone app" (compared to hailing a taxi) as a major advantage of the use of Uber/Lyft. Both users and non-user highly rate the "prefer[ence] to have/use their own vehicle" as the strongest limiting factor to the adoption of these technology-enabled services. The preference to use their own vehicle

is stronger among non-users and infrequent riders who use these services less than once a month.

The salience of cost and personal-vehicle preference as limiting factors suggests a promising future for on-demand rides services –if these services can reduce their prices and shorten waiting times. Pooling services are the primary strategy to reduce prices, though more research is needed to determine the price elasticity for different groups of travelers. Fortunately, pooling is a case where the public interest seems to align well with business interests. Uber and Lyft executives widely assert that they are strongly committed to pooling services as a way to increase ridership, revenue and profits (Sperling et al, 2018, p189-196).

In addition, we analyze the self-reported information on the effects that the use of Uber and Lyft have on other travel modes, as reported by the survey respondents. The adoption of ridehailing tends to reduce the amount of driving made by both frequent and non-frequent users. The use of these services also substitutes for some trips that would have otherwise been made by transit or active modes. The latter substitution effect is stronger among frequent users, those who live in zero-/deficient-vehicle households and those who are more multimodal. Somewhat concerning from the perspective of environmental sustainability and the promotion of active lifestyles, a larger proportion of millennials report that the use of ridehailing reduced the amount of walking and biking they do.

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

To better understand the potential impact of the use of Uber/Lyft on other components of travel behavior while controlling for the effects of sociodemographics and other confounding factors, we tested several model structures, including (a) a public transportation frequency model (which includes the use of Lyft/Uber as an explanatory variable), (b) a seemingly unrelated bivariate probit model and (c) a bivariate recursive probit model of the frequency of use of Uber/Lyft and the frequency of use of public transit for non-commute purposes. We find that public transportation frequency is largely determined by sociodemographics, built environment characteristics and the use of smartphone-based transportation apps. Frequent users of Uber and Lyft are more likely also to use public transportation more frequently, though this might not entail a causality relationship; rather, it might be the impact of other latent constructs or lifestyle orientation (e.g., mobility or modality style: some users might be more inclined to use both public transportation and Uber/Lyft frequently). The three types of bivariate models that were estimated lead to somewhat similar results: we find that the

frequency of use of Uber/Lyft and the frequency of use of public transit are significantly (and positively) correlated. This confirms that there are some unobserved factors that positively impact the frequency of use of both Uber/Lyft and public transportation. More investigation is required to better understand the true nature of this relationship (which cannot be fully explored through the analysis of cross-sectional data), and to identify the impacts of different lifestyle and mobility styles and the potential causality links between the use of Uber/Lyft and the use of public transportation.

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

Moving forward, there will be increasing need to coordinate policy making and incentives in order to harvest the potential benefits of these services, while reducing the negative effects. The greatest public benefits would come from pooling –reduced traffic congestion, road infrastructure costs, greenhouse gas emissions, and parking demand –which suggests policymakers need better understandings of who might use pooling services and what incentives and policies would be most effective at encouraging them to do so. In the next stages of our panel study we will be addressing these questions.

More studies are needed to help researchers and professionals understand the on-going transportation transformation and how to guide it to a better future. In future stages of this research, we plan to expand our analysis and apply more nuanced analytical approaches to investigate the behavioral changes in more disaggregated way. For example, we plan to employ latent-class choice modeling techniques to capture structural heterogeneity in travelers' decisions towards the use of various means of transportation. Further, the availability of longitudinal data in the future steps of this panel study will allow us to study the evolution of these travel patterns over time and, for example, disentangle the causality relationships among the adoption of these services, other components of travel behavior and eventual changes in household vehicle ownership.

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