Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area

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Abstract

Emerging technologies and services stand poised to transform the transportation system, with large implications for energy use and mobility. The degree and speed of these impacts depend largely on who adopts these innovations and how quickly. Leveraging data from a novel survey of San Francisco Bay Area residents, we analyze adoption patterns for shared mobility, electrified vehicle technologies, and vehicle automation. We find that ride-hailing and adaptive cruise control have penetrated the market more extensively than have electrified vehicles or car-sharing services. Over half of respondents have adopted or expressed interest in adopting all levels of vehicle automation. Overall, there is substantial potential for market growth for the technologies and services we analyzed. Using a county fixed effects regressions, we investigate which individual and location-level factors correlate to adoption and interest. We find that, although higher-income people are disproportionately represented among current adopters of most new technologies and services, low- to middle-income people are just as likely to have adopted *pooled* ride-hailing. Younger generations have high interest in automated and electrified vehicles relative to their current adoption of these technologies, suggesting that young people could contribute substantially to future market growth—as they are doing for ride-hailing. We find no evidence that longer commutes present a barrier to plug-in electric vehicle adoption.

Finally, women are less likely than men to adopt and/or be interested in adopting most new transportation technologies, with the exception of ride-hailing; designing or marketing technologies with women's preferences in mind could contribute to future market expansion.

Highlights:

- Novel data from the San Francisco Bay Area obtained from the WholeTraveler study.
- Highest adoption rates are for ride-hailing services and adaptive cruise control.
- High interest in automated and plug-in electric vehicle technologies.
- Adoption and interest mediated by age, income, gender, and commute distance.

Keywords: Transportation Decisions, Technology Adoption, Ride-Hailing, Automated Vehicles, Car-Sharing, Electric Vehicles

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1. Introduction

The transportation system is quickly evolving as new technologies and services emerge. Ride-hailing and car-sharing, electrification technologies, and technologies that increasingly automate the task of driving are a growing reality. Such emerging transportation innovations may have a large impact on future energy use and sustainable mobility patterns—depending on how they are adopted. Our goal is to understand what drives the adoption of and interest in such technologies and services to gain insight into who the current users are, who they are likely to be in the future, and how the transportation system might optimally evolve with increased sustainability and equitable access to these technologies and services.

The need for this understanding is evident in a growing area of research that relies on transportation system simulation models to probe the potential impact of emerging technologies on energy demand and transportation patterns. Although these studies can inform public and private energy and transportation planning, recent analyses using some of these models depict vastly uncertain futures and thus do little to guide practical planning efforts. Stephens et al. (2016), for example, characterize the uncertainty surrounding potential energy impacts of automated vehicles (AVs) alone as ranging from a 60% reduction in energy demand to a 200% increase. Much of this uncertainty stems from the need to understand the potential adoption and use decisions of millions of people across the U.S. and around the world—not just for a single transportation technology, but for the portfolio of transportation modes that meet their travel needs. To reduce this uncertainty, transportation system models need consumer data and analyses that enable a more refined understanding of how human behavior drives demand for new transportation technologies and services.

In this paper, we present results that can help clarify relevant behaviors to better underpin these simulation models, inform system planners, and generate insights that can suggest pathways for increasing access to emerging transportation technologies and innovations. We focus on the following emerging technologies and services: shared-mobility services including ride-hailing (single-rider and pooled) and car-sharing, electrified vehicles including hybrid electric vehicles and plug-in electric vehicles (PEVs), and three different levels of AV technologies. Our analysis focuses on four types of factors that we hypothesize, based on our literature review, can explain adoption of and interest in these emerging developments: demographics (e.g., age, income, gender), location-specific factors (e.g., walkability, population density, commute distances), preferences for mode attributes (e.g., social interactions, convenience), and human characteristics (e.g., risk preferences, personality). Some factors have been found to be important for several but not all emerging transportation technologies and services. Other factors are understudied in the context of transportation, especially those found to be important for other emerging technologies and services in general, such as risk preferences. We help fill the knowledge gap by more fully exploring select factors that may influence the adoption of emerging transportation technologies and services. In addition, we distinguish current adoption and interest in future adoption, and we conduct the analysis across multiple technologies and services for the same pool of respondents.

We leverage a novel dataset generated by the WholeTraveler Transportation Behavior Study survey. We developed this survey with the support of the U.S. Department of Energy's (DOE's) Energy Efficient Mobility Systems (EEMS) program as part of the SMART Mobility Consortium, which strives to clarify energy implications and opportunities related to advanced mobility solutions.[1] We used the survey to elicit the mobility decisions and characteristics of 1,045 households in the San Francisco Bay Area, which is a leading region for the introduction of advanced transportation solutions.

[1] More information about the SMART Mobility Consortium can be found in Appendix A in the supplementary materials.

In Section 2 of the paper, we define our target technologies and services, and we review relevant behavioral studies. In Section 3, we provide detail on the WholeTraveler Transportation Behavior Study survey, our empirical approach, and our data. Section 4 presents our results, while Section 5 discusses the main takeaways and characterizes the contribution of the study. Section 6 concludes.

2. Background and Literature Review

In this section, we more carefully define each of the categories of transportation technologies we analyze (shared mobility, electrified vehicles, and AVs), and we summarize existing literature that addresses the relationship between adoption of these technologies and the four explanatory-factor groups that thematically emerge from this literature: demographics, location-specific factors, preferences over mode attributes, and personality and risk characteristics.

2.1 Shared Mobility

Shared mobility—via ride-hailing, car-sharing, and other shared services—helps travelers meet mobility needs without reliance on personally owned vehicles. Ride-hailing allows users to request a driver and car for a trip from any given origin to their destination via a smartphone app. Traditionally, shared, on-demand transportation service has been provided by taxi fleets, but newer options such as transportation network companies (e.g., Uber and Lyft) have attempted to offer their services at a lower price-point and with more convenience via their apps, which has increased the impact and use of shared mobility. In contrast, car-sharing allows users to drive, for short periods, vehicles that are shared across other users of a car-share service. All shared-mobility services are more common in urban areas and may be used with other transportation options to enable greater adoption.

Our survey targeted three forms of shared mobility. We included two forms of ride-hailing: single-rider services (e.g., UberX or standard Lyft) and pooled services (those serving multiple riders with similar origins and destinations via a single driver/vehicle at a reduced cost, such as Uber Pool or Lyft Shared). The pooled option for ride-hailing is often referred to in the literature as "ride-splitting" (e.g., Shaheen, Cohen and Zohdy 2016, Department of Energy 2017). We also included car-sharing, which is less broadly adopted relative to ride-hailing, but reflects an alternative model of shared mobility currently available.

Most studies have found that users of ride-hailing and car-sharing services tend to be disproportionately younger, higher income/wealthier, and college educated with fewer or no children at home (Alemi et al. 2018; Clewlow and Mishra 2017; Dias et al. 2017; Kooti et al. 2017; Smith 2016; Cervero et al. 2007; Namazu and Dowlatabadi 2018), although car-sharing adopters can tend to be older (Cervero et al. 2007). In studies of ride-hailing, gender has either not been considered (Clewlow and Mishra 2017; Dias et al. 2017), or no effect has been found (Smith 2016), although some studies have found that women tend to be more likely to use ride-hailing (Alemi et al. 2018; Kooti et al. 2017). A general trend of younger generations away from car ownership and toward use of shared or on-demand mobility may point to larger societal changes shaping mobility preference. The phrase, "You are what you can access," illustrates this perspective, in contrast to an older paradigm that may more closely link identity with ownership (Belk 2014).

Lee et al. (2018) found that perceived risks, benefits, and trust related to a ride-hailing platform mediate preference for the mode. The ability to quickly summon a ride from an app—

which provides transparent travel routing, driver ratings, and communication channels—may improve perceptions of safety. Moreover, most ride-hailing is conducted via traditional automobiles, a strongly established transportation mode in the U.S. (Clewlow and Mishra 2017).

The use of ride-hailing and car-sharing services is higher in urban areas than in rural areas (Becker et al. 2017; Smith 2016). Therefore, studies of location-specific factors have concentrated on exploration of trip origins and destinations within an urban setting, and on location-specific pricing, which may rise or fall in conjunction with time of day and other events (Rayle et al. 2016). Ride-hailing service can be in high demand at peak times and in certain locations, such as airports, areas of concentrated entertainment, or sporting venues. Similarly, limited parking, availability of good public transit, high density, and mixed-use neighborhoods are associated with more car-sharing (Klintman 1998; Muheim and Reinhardt 1999; Clewlow and Mishra 2017).

Personality[2] plays a key role in technology adoption (Amichai-Hamburger and Vinitzky 2010; Ehrenberg et al. 2008), and it has been found to have a mixed influence on behaviors related to shared mobility. Greater extraversion is related to more willingness to engage in the sharing economy, whereas no relationship has been found with engagement and openness (Roy 2016). Those who rate high on agreeableness worry less about unpleasant interpersonal incidents occurring across a wide range of transportation modes (e.g., bus, metro, taxi, tram) and hence

[2] According to the American Psychological Association, personality refers to “individual differences in characteristic patterns of thinking, feeling and behaving” (Khatibi and Khormaei 2016). The *Big Five* dimensions of personality are extraversion (vs. introversion), agreeableness (vs. antagonism), conscientiousness (vs. lack of direction), neuroticism (vs. emotional stability), and openness (vs. closedness to experience) (Pervin and John 1999). Extraversion is associated with gregariousness, assertiveness, activity, excitement seeking, positive emotions, and warmth. Agreeableness is marked by trust, straightforwardness, altruism, compliance, modesty, and tender-mindedness. Conscientiousness is marked by competence, order, dutifulness, achievement, self-discipline, and deliberation. Neuroticism is associated with anxiety, angry hostility, depression, self-consciousness, impulsiveness, and vulnerability. Openness is marked by appreciation of unusual ideas, fantasy, aesthetics, emotions, and a variety of experiences. People possess all five dimensions, and they vary in terms of what proportion of each that they have.

may be more willing to use shared transportation (Backer-Grøndahl et al. 2009). However, those rating high in neuroticism worry more about these types of incidents and are more likely to change their mode or route to avoid them (Backer-Grøndahl et al. 2009). Somewhat related to several of these personality factors, some studies have suggested that shared transportation can deepen human connectedness, and thus individuals may be motivated (or not) to use shared transportation depending on their desire for connectedness (Crewe and Forsyth 2011; McFarland 2015; Pangborn-Dolde et al. 2015).

Levels of risk acceptance also affect adoption of shared-mobility services. For instance, older people who are making decisions about adopting new technologies and services are often impacted by their perception of risk (Beaud et al. 2016; Dixit et al. 2015; Czaja et al. 2009; Jackson and Jucker 1982; Mitzner et al. 2010; Pan and Jordan-Marsh 2010; Selwyn 2004; Wolf and Seebauer 2014). Watanabe et al. (2016) and Saelens et al. (2003) found that risk-averse people make less use of multiple modes during a single trip, suggesting that new mobility options may not serve well as a first-mile/last-mile complement for public transit to those who are risk averse.

2.2 Electrified Vehicles

We consider vehicle technologies that use electricity in place of petroleum-based fuels. These vehicles can significantly reduce carbon emissions and overall energy use, especially when relatively efficient means are used to generate the power they use. Specifically, our survey used two terms for the electrified vehicle technologies of interest. “Hybrid vehicles (gasoline-electric)” were meant to represent vehicles propelled by both an internal combustion engine and an electric motor powered by batteries that are charged by the engine and regenerative braking.

“Plug-in electric vehicles” could include battery electric vehicles (BEVs), which have only electric motors powered by batteries and require external charging to run, and plug-in hybrid electric vehicles (PHEVs), which combine an external combustion engine with a motor powered by batteries that can also be charged externally. We recognize that, based on the survey wording, respondents could have classified PHEVs as either “hybrid vehicles (gasoline-electric)” and/or “plug-in electric vehicles.” In the interest of simplicity, for the remainder of the paper, we refer to the electrified vehicle technology categories as “hybrids” and “plug-in electric vehicles” (PEVs) to match the analysis and discussion with the wording of the survey. We separate our hybrid and PEV analyses to reflect the distinction made in the survey. However, interpretation of the results distinguishing these two categories should be done cautiously, because the existence of PHEVs means we may not be able to precisely distinguish the technology types depending on how respondents interpreted the questions.

Much of the recent literature regarding preference for electrified vehicles has concentrated on stated-preference studies for PEVs, attempting to identify how information can strengthen interest among potential car buyers (Liao et al. 2016; Cherchi 2017). Preferences for PEVs may be shaped by forces beyond purchase economics, including a sense of societal value in ownership (Haugneland and Hauge 2015) and—because of the smaller number of moving parts in PEV motors as compared to internal combustion engines—the sense that they are less expensive to fuel and maintain (Mi and Masrur 2018).

Convenient availability of charging stations may also be important for PEV adoption and use. Electricity supply is nearly ubiquitous in the U.S., even if relatively fast-charging Level 2 or Level 3 PEV-charging stations are not. Much of the research in this area specific to location has used simulation models to identify strategies for siting fueling stations, to optimize the balance between demand, current PEV range, charging time requirements, and grid impacts (Sadeghi-Barzani et al. 2014; Luo et al. 2017). Some of this work has identified the difference in vehicle charging needs by location, such as residence location (urban, multi-unit dwellings vs. suburban homes), and by trip type (long-distance highway trips vs. short urban trips) (Wood et al. 2017). The simulation models usually include assumptions about charging demand. However, because PEV ownership has not yet reached a large segment of the population, there are many gaps in understanding behaviors associated with charging.

Many recent studies have found that users of electrified vehicles tend to be disproportionately male, younger, higher income/wealthier, and college educated with fewer or no children at home (Caperello and Kurani 2011; Langbroek et al. 2017; Nayum et al. 2016; Plötz et al. 2014), although some exceptions to these general patterns emerge; for example, Ziefle et al. (2014) found women and older generations to be more interested in electrified vehicles. Much of the research on these vehicles with respect to risk focuses on "range anxiety" related to the constrained range of BEVs and the relative sparseness of vehicle-charging infrastructure as compared to the gasoline refueling infrastructure used by internal combustion engine vehicles. The findings suggest that people who are more concerned about range are less likely to be interested in buying a BEV. However, those who adopt a BEV seem to experience much less anxiety about range over time (Franke et al. 2012; Neubauer and Wood 2014). Skippon and Garwood (2011) found that people tend to see the typical PEV driver as rating high on agreeableness, conscientiousness, and openness, because high-agreeableness individuals tend to care more about others, high-conscientiousness individuals like planning ahead, and high-openness individuals are interested in new things.

2.3 Automated Vehicles

SAE International defines six levels of automation from no automation (0) to full automation (5).[3] Each level of automation provides increased assistance to drivers and reduced levels of driver input.

Our survey defines three categories of automation. With "adaptive cruise control (ACC)," a vehicle "brakes and accelerates to match the speed of the vehicle in front (only on highways), but requires driver to steer," corresponding to SAE automation level 1. A "partially automated" vehicle "automatically brakes and accelerates, and additionally steers itself sufficiently to stay in a lane (only on highways), but requires the driver to be paying attention, to change lanes and be available to override," corresponding to SAE automation levels 2–3. When it is "fully automated," a "vehicle drives itself and does not require driver to pay attention (i.e., rider could sleep, read, work, or otherwise not pay attention to the road)," corresponding to SAE automation levels 4–5.

Because the degree of automation changes how the vehicle is controlled, it affects the energy use and safety of vehicles, and it may affect how people purchase and use vehicles. In particular, fully automated vehicles are being considered by ride-hailing services as a way to lower the costs of shared mobility.

Studies have found that early and potential adopters of partially and fully automated vehicles tend to be male, technology savvy, and higher income/wealthier; have greater car-crash experience and greater willingness to pay for new technologies; and be less influenced by whether friends adopt the technology (Bansal and Kockelman 2016; Fortune.com 2018; Investopedia.com 2018; Payre et al. 2014). Research on age is mixed. Some studies have found

[3] The formal definitions for these levels are included in Appendix B in the supplementary materials.

that older adults may be interested in fully automated vehicles for increased mobility (Abraham et al. 2016; Haboucha et al. 2017), whereas others have found that older individuals express less interest, perhaps due to concerns about learning to use the new technology and losing the pleasure of driving (Bansal and Kockelman 2018).

From a user standpoint, AVs may enable improved access to mobility, convenience, safety, and reduced stress while traveling, reducing the drudgery and human error associated with driving. However, at the present state of development, concern over the safety of AVs exists, and the ethics issues surrounding machines making life-and-death decisions are considerable (Bonnefon et al. 2016). User attitudes toward the technology may also impact how it is deployed. Applying AV technology to shared mobility could reduce overall vehicle ownership, with users soliciting rides on an as-needed basis and shared AVs serving a greater number of passengers as compared to private ownership. A study found that shared AVs could be an inexpensive mobility on-demand service, potentially improving mobility access, if the balance between cost, waiting time, and travel time can be optimized for user experience (Krueger et al. 2016). Regardless of the mix of private and shared AVs, a recent survey found that people identify advantages in AV technologies for which they are willing to pay a premium, anticipating that AVs will constitute a substantial portion of the vehicle fleet by 2045 (Bansal and Kockelman 2017).

The earliest existing fully automated vehicles are low-speed shuttles with a capacity of about eight passengers, operating on defined routes in campus or similar settings where they are likely to encounter only minimal traffic. Such AV shuttles may be a viable option for serving first/last-mile roles in conjunction with public transit (Winter et al. 2016; Scheltes et al. 2017). From the standpoint of the potential impact of AVs by geography, there are both positive and negative potentials. AVs could enable densification in urban cores as the need to own, drive, and park private vehicles declines because of access to shared AVs. On the other hand, primarily private AVs may encourage urban sprawl (Fagnant and Kockelman 2015; Milakis et al. 2018). By replacing the burden of driving with time that may be spent for productivity, entertainment, or even for sleeping, AVs may enable people to live farther from work, increasing commute distances and energy expended.

Several psychosocial factors have been found to influence the use of AV technologies. "High sensation seekers"—those who drive faster, leave less space between vehicles, and brake more abruptly—may be less likely to use ACC and might adapt their behavior in a partially or fully automated vehicle by driving less carefully (Payre et al. 2014). People with greater openness to new technologies and stronger environmental views are more likely to intend to adopt AVs, whereas those with a stronger locus of control and greater enjoyment derived from driving are less likely (Haboucha et al. 2017; Sun et al. 2017; Zmud and Sener 2017). Moreover, these factors influence people's willingness to pay for the technology, with research suggesting that people are not willing to pay much more ($0–$3,000) for an AV than for a conventional vehicle (Zmud and Sener 2017). Hohenberger et al. (2017) found that increased feelings of self-enhancement from the use of AVs reduced AV-related anxiety and ameliorated the effect of anxiety on reducing positive feelings toward the technology.

An emerging factor that may prove important for adoption of AVs is the extent to which an individual is a "risk-lover" or "risk-taker." A recent study by Hulse et al. (2018) found no difference with respect to risk perceptions about various automation technologies (e.g., automated trains versus cars) among risk-takers, perhaps because the technology is touted as being "safe" compared to other modes of transportation. However, more research is needed to better understand the extent to which risk matters for the adoption of the technology, particularly in light of recent publicity about fatal car accidents involving partially automated technologies.

3. Approach for Analyzing Adoption and Interest Patterns

3.1 WholeTraveler Transportation Behavior Study Survey

The data presented in this paper are derived from a web-based survey with questions related to a variety of demographic, preference, life history, and personality and psychological factors as well as technology adoption and interest.[4] The online instrument is part of a larger WholeTraveler Transportation Behavior Study that aims to understand travel choice patterns, preferences, and decision-making processes in the context of new mobility technologies, with a focus on the San Francisco Bay Area.

A sample of randomly selected addresses in the nine Bay Area California counties[5] was recruited to respond to an online survey via a mailed invitation letter followed by a reminder postcard. The invitation asked the household member who most recently had a birthday and is above the age of 18 to respond to the survey. To complete the survey, the respondent went online through a web browser on a desktop or laptop computer. The survey was only administered in English. Respondents received a $10 Amazon gift card for completing the survey.

Recruitment letters were sent to 60,000 households. Of these, 997 residents (1.7%)[6] completed the entire survey, and 48 completed the first portion of the survey instrument (the part used for this analysis) for a total of 1,045 responses. All responses were completed during the

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[4] More detail on this study and the DOE program it is funded by can be found in Appendix A in the supplementary materials.

[5] Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, and Sonoma Counties.

[6] The response rate is consistent with other implementations using similar unsolicited mailings to recruit, and with similar incentive payment levels. For example, the 2015-2017 California Vehicles Survey has a 1.5% response rate overall (California Energy Commission 2018).

period between March and June 2018, with a median completion time for those that finished the full survey of 28 minutes.

A key limitation of this research is that our sample was constrained to the San Francisco Bay Area, and those who answered the survey were disproportionately highly educated and high income even within the Bay Area. However, female response to the survey was high and more representative of the local population, suggesting that our findings reflect well the adoption of and interest in our target transportation modes among female residents in the surveyed area. An advantage of focusing on this geographic area is that it has been the subject of previous studies using other data-collection approaches (e.g., Clewlow 2016; Cervero and Tsai 2004; Alemi et al. 2018). Thus, it is relatively well characterized with respect to its strengths and weaknesses as a leading indicator for wider geographic demand.

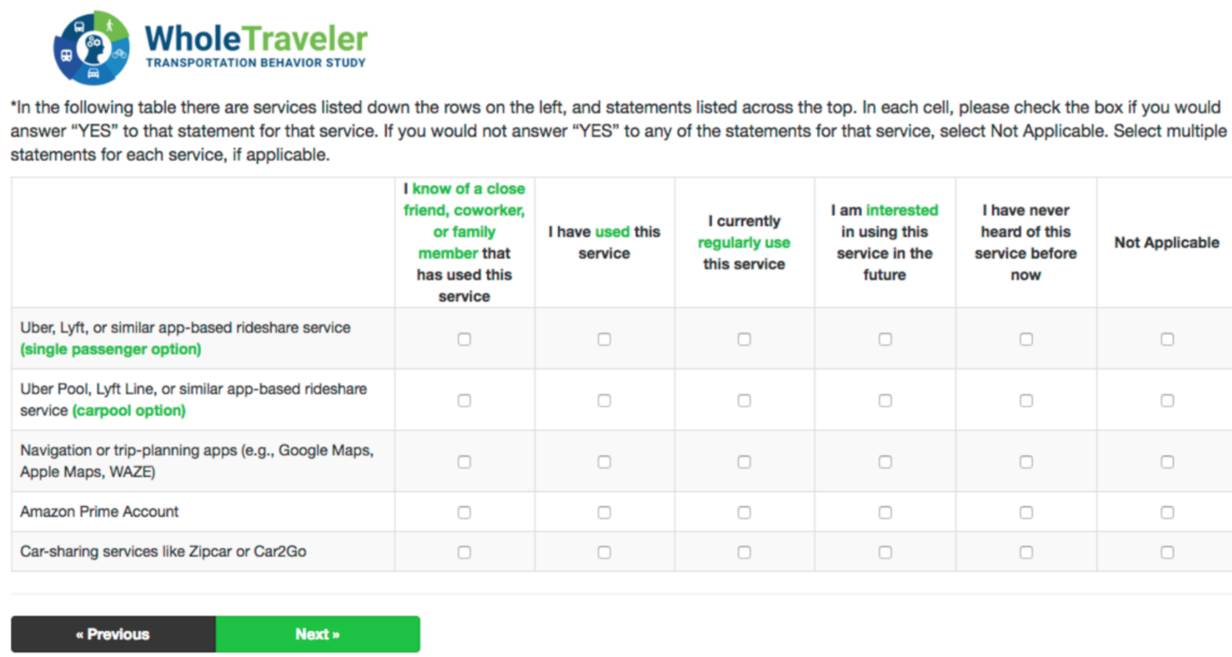
The full WholeTraveler survey instrument can be found in Appendix C in the supplementary materials. The survey included questions around each user's travel behaviors, mode choices, preferences over mode attributes, commute locations, car ownership, e-commerce behavior, and interest in new mobility technologies and services. It also included questions associated with demographic and household characteristics, personality traits, risk attributes, and a life-history calendar that looked at life events and travel behaviors undertaken while the respondent was between the ages of 20 and 50. Those taking the survey were then offered the chance to complete a second phase of the survey that recorded their movements and travel for one week using the Global Positioning System (GPS).

Table 1 summarizes the subset of questions from the survey relevant to our present study. The choice of the explanatory variables used in the analysis was primarily motivated by the existing literature reviewed in Section 2. A detailed description of the derivation and use of the outcome and explanatory variables is presented in Section 3.3.

Table 1: High-level summary of survey questions used in this analysis

Survey Instrument Category	Question Summary	Analysis Relevance
Emerging technologies	Familiarity/adoption/interest in hybrid vehicles, PEVs, ACC, partial automation, full automation, ride-hailing services (single-rider or pooled), car-sharing, and some other technologies and services	Stated interest in and adoption of emerging technologies
Demographics	Year of birth, gender, level of education, annual household income, number of children under 8 years of age, and a number of other demographic and household characteristics	Observable demographic characteristics of the participants
Preference over mode attributes	Importance of mode characteristics to user's transportation choices: short travel time, low cost, predictable cost, predictable arrival time, ability to make multiple stops, low hassle, safety, environmental impact, social interactions	Stated determinants of current adoption choices and mode use
Personality	Questions to determine personality factors: extraversion, agreeableness, conscientiousness, neuroticism, openness to experience	Personality factors
Location-specific factors	Specific addresses for residence location and primary destination	Location characteristics of residence and destination (population density and walk score) and distances from residence to primary destination
Risk attitude	Repeated hypothetical choices between a certain prize amount for sure or taking a 50-50 chance at getting a higher prize amount with varying value trade-offs	Risk attitude

Figure 1 shows an example set of questions from the emerging technologies category. The respondents were given a technology or service and asked to indicate all statements that applied to their experience with the technology. They could choose whether they knew of someone who had used it, whether they themselves had used it, whether they regularly use it or owned it, and/or whether they were interested in using the service or purchasing it in the future. They could also indicate whether they had never heard of it or that it was not applicable. We focus our primary analysis on those who reported that they are regular users/owners of a service or technology, and those who selected that they are interested in using/purchasing it in the future.


WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In the following table there are services listed down the rows on the left, and statements listed across the top. In each cell, please check the box if you would answer "YES" to that statement for that service. If you would not answer "YES" to any of the statements for that service, select Not Applicable. Select multiple statements for each service, if applicable.

	I know of a close friend, coworker, or family member that has used this service	I have used this service	I currently regularly use this service	I am interested in using this service in the future	I have never heard of this service before now	Not Applicable
Uber, Lyft, or similar app-based rideshare service (single passenger option)	☐	☐	☐	☐	☐	☐
Uber Pool, Lyft Line, or similar app-based rideshare service (carpool option)	☐	☐	☐	☐	☐	☐
Navigation or trip-planning apps (e.g., Google Maps, Apple Maps, WAZE)	☐	☐	☐	☐	☐	☐
Amazon Prime Account	☐	☐	☐	☐	☐	☐
Car-sharing services like Zipcar or Car2Go	☐	☐	☐	☐	☐	☐

« Previous Next »

Figure 1: Sample question eliciting degree of adoption and interest in adopting

3.2 Data Preprocessing

To screen out any respondents who completed the survey only to receive the Amazon gift card incentive, and therefore clicked through responses without reading questions or answering meaningfully, we dropped all respondents with a response time less than 12 minutes. This removed 19 survey responses (1.82% of the data).

Next, we addressed a limited number of omitted responses to questions from which preference-over-mode-attribute variables are obtained. Cases in which respondents chose "not applicable" for variables in the preference-over-mode-attribute category were recoded with a score of zero, giving zero value to characteristics that a respondent deemed as factors that are not relevant to their commute mode choice.[7] Appendix D in the supplementary materials reports results where these values are instead assigned a score of three or omitted entirely, which shows that the main conclusions drawn from the models are unaffected. For a limited number of cases, population density of a primary destination was zero (because the relevant census block group is completely non-residential); for the analysis, all zero values of primary destination population density are replaced with the sample average value. This is a very limited change that allows the cases to be included in mathematical comparisons. These steps result in a final set of 1,026 observations that are used in the analysis.

3.3 Data Analytical Approach

To capture the distinction between current adoption and interest in future adoption, we define two sets of dependent variables and estimate linear probability model ordinary least squares (OLS) regressions for each analyzed technology or service.[8] The dependent variables are (1) Adopted: defined as an indicator variable equal to one if the respondent reported owning a given emerging technology or regularly using an emerging service, zero otherwise; and (2) Interested in Adopting: defined only for the subsample that has not already adopted the service or technology, this indicator variable is equal to one if the respondent reported interest in using the service or owning the technology in the future. The first set represents the segment that has already adopted, while the second represents the adoption potential of these technologies and services among those who have not already adopted.

[7] Six of eight questions in the preference-over-mode-attribute category have fewer than 20 missing values. Only predictable cost and multiple stops have more, at 27 and 43, respectively. This results in 56 observations that would otherwise be omitted from analysis (7.3% of the reduced sample).

[8] Analyses were conducted using a Logit regression as well, with consistent results between that and the OLS regressions. Estimates from the Logit regressions can be found in Appendix D in the supplementary materials.

The summary statistics for dependent variables used in this study are provided in Table 2. Both sets of variables are defined from responses to survey questions 1.11–13, which can be viewed in Appendix C in the supplementary materials; Figure 1 shows question 1.13.

Table 2: Summary statistics of outcome variables

	N	Mean	SD	Min	Max
Adopted: Ride-hail Single	1,026	0.27	0.44	0	1
Adopted: Ride-hail Pooled	1,026	0.18	0.38	0	1
Adopted: Car-Sharing	1,026	0.03	0.16	0	1
Adopted: Hybrid	1,026	0.16	0.37	0	1
Adopted: Plug-in Electric	1,026	0.06	0.25	0	1
Adopted: Adaptive Cruise Control	1,026	0.17	0.38	0	1
Adopted: Partially Automated	1,026	0.04	0.20	0	1
Interested in Adopting: Ride-hail Single	752	0.27	0.44	0	1
Interested in Adopting: Ride-hail Pooled	846	0.20	0.40	0	1
Interested in Adopting: Car-Sharing	1,000	0.19	0.39	0	1
Interested in Adopting: Hybrid (Gas-Electric)	864	0.426	0.49	0	1
Interested in Adopting: Plug-in Electric	960	0.53	0.50	0	1
Interested in Adopting: Adaptive Cruise Control	851	0.46	0.50	0	1
Interested in Adopting: Partially Automated	984	0.47	0.50	0	1
Interested in Adopting: Fully Automated	990	0.51	0.50	0	1
Max Observations	1,026				

To analyze the impact of explanatory factors on adoption and interest in adoption of technologies and services, we estimate the following model:

$$Y_{igc} = \alpha + \mathbf{X}'_{igc}\boldsymbol{\beta} + \mathbf{P}'_i\boldsymbol{\theta} + \epsilon_i \tag{1}$$

Equation (1) describes the outcome for individual i in census block group g in county c as a function of individual and geographic factors, personal-level characteristics, and an idiosyncratic error.

$$\begin{aligned}\mathbf{X}'_{igc}\boldsymbol{\beta} = {}& \beta_1 Child_i + \beta_2(> 4yr\ College)_i + \beta_3 Female_i \\ & + \beta_4 WalkScore_i + \mathbf{BirthDec'}_i\boldsymbol{\eta} + \mathbf{PopDens'}_{gc}\boldsymbol{\delta} \\ & + \mathbf{PrimaryDistance'}_i\boldsymbol{\lambda} + \mathbf{HH\ Inc'}_i\boldsymbol{\gamma} + \mathbf{C}_c\end{aligned} \tag{2}$$

The first explanatory variable vector in Equation (1) captures the demographic and location-specific factors and is given by Equation (2) wherein the first three terms are dummy variables, equal to one when there is a child under age 8 in the home, the respondent has more than a bachelor's degree education, or the respondent identifies as female. We include three types of location-based factors in our analysis. First, the walk score of the residence (*WalkScore*)[9] is included to account for access to nearby amenities (e.g., grocery stores and restaurants). Walk scores are computed using an algorithm that calculates distance to the nearest amenity in a set of categories, where "amenities within a 5 minute walk (.25 miles) are given maximum points. A decay function is used to give points to more distant amenities, with no points given after a 30 minute walk."[10] All categories of amenities are given equal weighting, then normalized and summed to produce a number ranging from 0 to 100. This measure is included to directly reflect the feasibility of walking as a mode choice, because walk scores have been found to strongly correlate with nearby access to reported primary commute destination types including grocery stores, fitness facilities, restaurants, coffee shops, libraries, and retail (Carr et al. 2011) and access to public transportation in the form of train and bus stop counts (Koohsari et al. 2018). The second location-based factor is population densities in the census block group of both the residence and the primary destination (*PopDens* in 1,000 people per square mile), reflecting accessibility and likelihood of public transit use or walking (Reilly and Landis 2002) and acting as "proxies for variables that represent the quality of the transit service" (Chen et al. 2008).[11] The third location-based factor is commute distances (*PrimaryDistance)*,

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[9] See https://www.walkscore.com/professional/.
[10] See https://www.walkscore.com/methodology.shtml.
[11] Residential and workplace population densities are also a significant factor in determining San Francisco Bay Area vehicle choice (Kockelmann 1997); the decision to walk, bike, or take public transit in Hong Kong and Boston (Zhang 2004); vehicle miles traveled in Portland, Oregon (Sun et al. 1998) and nationwide (Chatman 2003); and engagement in work and shopping trips by foot in Puget Sound (Frank and Pivo 1994) and general walking trips in

determined by the address of the home and the primary destination (P.D.) provided by each participant in the survey and calculated using the Google API to reflect the distance in miles via driving route. This distance encompasses the operating costs, travel time in which the respondent would use the technology or service, and the range for BEV use. *PrimaryDistance* is captured by three included dummy variables indicating whether the respondent's primary commute distance falls into the following partitioned categories: 10 to 20 miles, 20.01 to 50 miles, and above 50 miles, while less than 10 miles serves as the omitted category.

Among the remaining factors, *HH Inc* represents annual household income before taxes and also enters as dummy variables after being partitioned into three categories: $75,000 to $150,000, $150,001 to $200,000, and above $200,000, with less than $75,000 as the omitted category. These bins approximate the quartiles of household income within the sample, with some slight deviation given the coarseness of the income categories respondents could select in the survey. The age of the respondent is accounted for through the inclusion of dummy variables indicating the decade in which the respondent was born (*BirthDec*): 1930s, 1940s, 1950s, 1970s, 1980s, and 1990s, with 1960s being the omitted category. C_c is a vector of county fixed effects, included to absorb unobservable differences in transportation mode choices and accessibility across counties in the San Francisco Bay Area. Summary statistics of demographic and location-specific variables are presented in Tables 3 and 4, respectively.

Table 3: Summary statistics of demographic and household variables

	N	Mean	SD	Min	Max
Born 1930s	1,026	0.01	0.12	0	1
Born 1940s	1,026	0.08	0.26	0	1
Born 1950s	1,026	0.14	0.35	0	1
Born 1960s	1,026	0.18	0.38	0	1
Born 1970s	1,026	0.20	0.40	0	1

Baltimore and Washington DC (Mahmoudi and Zhang 2018). Additionally, residential population density can impact availability of street parking, a factor found to dramatically affect car ownership in New York City (Guo 2013).

Born 1980s	1,026	0.28	0.45	0	1
Born 1990s	1,026	0.11	0.31	0	1
Any Children < 8yrs	1,026	0.16	0.36	0	1
HH Income < 75K	875	0.27	0.44	0	1
HH Income [75K,150K)	875	0.34	0.47	0	1
HH Income [150K,200K)	875	0.15	0.36	0	1
HH Income ≥ 200K	875	0.25	0.43	0	1
> 4yr College Ed.	1,026	0.45	0.50	0	1
Female	989	0.49	0.50	0	1
Max Observations	1,026				

Table 4: Summary statistics of location-based variables

	N	Mean	SD	Min	Max
Res. Pop. Density	1,026	13.20	15.09	0.01	169.292
P.D. Pop. Density	1,026	9.15	12.94	0.02	130.770
Walk Score	1,026	54.43	28.49	0	99
Distance to Primary Dest. (mi)	1,026	12.50	18.49	0	389.326
Dist. to P.D. ≤ 10mi	1,026	0.58	0.50	0	1
Dist. to P.D. (10,20] mi	1,026	0.21	0.41	0	1
Dist. to P.D. (20,50] mi	1,026	0.18	0.39	0	1
Dist. to P.D. > 50mi	1,026	0.03	0.16	0	1
Alameda County	1,026	0.25	0.44	0	1
Contra Costa County	1,026	0.14	0.35	0	1
Marin County	1,026	0.03	0.17	0	1
Napa County	1,026	0.001	0.10	0	1
San Francisco County	1,026	0.16	0.37	0	1
San Mateo County	1,026	0.08	0.27	0	1
Santa Clara County	1,026	0.23	0.42	0	1
Solano County	1,026	0.04	0.19	0	1
Sonoma County	1,026	0.06	0.23	0	1
Max Observations	1,026				

The second vector of explanatory variables in Equation (1) is specified in Equation (3), which first contains the vector of the preference-over-mode-attribute category variables (*ModeAttrib)* covering respondents' strength of preference for characteristics of transportation modes used on commutes to their primary destination. Respondents rated how important—on a scale of not at all important (1) to very important (5)—each of the following characteristics of transportation options are in their choice of modes: vehicle safety, low travel cost, low hassle, predictable travel time, short travel time, predictable cost, ability to make multiple stops during a trip, minimizing environmental impact, and the ability to interact with individuals outside of one's immediate social circle.[12]

$$\mathbf{P'}_i\boldsymbol{\theta} = \mathbf{ModeAttrib'}_i\boldsymbol{\pi} + \mathbf{BigFive\ Personality'}_i\boldsymbol{\tau} + \mathbf{Risk\ Preferences'}_i\boldsymbol{\omega} \quad (3)$$

The second and third vectors account for individual personality and risk preferences. The term *BigFive Personality* captures the Big Five personality dimensions (agreeableness, conscientiousness, extraversion, openness, and neuroticism), placing people on a scale of 1–5 for each characteristic. These Big Five personality scales were generated using the 10-question Big Five Personality survey measure (BFI-10). *Risk Preferences* accounts for respondents' preferences over a 50-50 lottery of winning \$100 or receiving nothing (a certainty equivalent of \$50), and a set amount of money for sure ranging from \$1 to \$90. We include an indicator bin for high risk aversion (corresponding to a price at which the respondent prefers the sure amount, or reservation price, of \$1–\$20), moderate risk aversion (\$30–\$40 reservation price), and risk loving (\$60 or higher reservation price), with risk neutrality (\$50) serving as the omitted group. Summary statistics for the preference-over-mode-attribute, personality, and risk variables are presented in Tables 5 and 6, respectively.[13]

[12] The environmental impact and social interaction variables are derived from two questions in the WholeTraveler survey instrument. First, in question 1.5 respondents were asked whether they view minimizing environmental impact and social interaction each as positive or negative attributes. If a respondent chose that those attributes were positive, they were then presented with "minimize environmental impact" and "ability to interact with others (other than close friends or family members)" in question 1.6 for evaluation of importance when determining mode choice. If they indicated they were negative attributes, the respondent was instead presented with "maximize environmental impact" and "not having to interact with other people (other than close friends or family)." Each respondent was shown only one version of the questions. For our analysis, we combine answers to the positive and negative responses to 1.6, coding a response to the negative form as a negative value from 1 to 5, and an answer to the positive version as a positive 1 to 5. Like the other importance variables, a "not applicable" response is coded as a zero.

[13] Appendix D in the supplementary materials presents regression results corresponding to running the model in Equation (1) including only the vector of variables defined in Equation (2). We provide these results to demonstrate the robustness of these factors to the inclusion and omission of Equation (3) regressors.

To confirm the robustness of our results and prevent spurious identification of predictors, we test combinations of predictor variable sets (demographics, preference over mode attributes, and personality/risk preferences) to ensure the identified significant predictors present consistently across model specifications.

Table 5: Summary statistics for preference-over-mode-attribute variables

	N	Mean	SD	Min	Max
Safety	1,026	4.25	1.08	0	5
Low Cost	1,026	3.80	1.23	0	5
Low Hassle	1,026	4.34	0.98	0	5
Short Time	1,026	4.32	0.97	0	5
Predict. Time	1,026	4.41	0.92	0	5
Predict. Cost	1,026	3.66	1.31	0	5
Multiple Stops	1,026	3.07	1.51	0	5
Min. Env. Impact	1,023	3.34	1.78	-5	5
Social Interaction	984	0.35	2.82	-5	5
Max Observations	1,026				

Table 6: Summary statistics for personality and risk variables

	N	Mean	SD	Min	Max
BFI-10: Extraversion	1,026	3.10	0.99	1	5
BFI-10: Agreeableness	1,026	3.74	0.70	1.7	5
BFI-10: Conscientiousness	1,026	3.97	0.82	1.5	5
BFI-10: Neuroticism	1,026	2.66	0.95	1	5
BFI-10: Openness	1,026	3.61	0.87	1	5
Risk Averse ($1-20 Reservation)	1,026	0.23	0.42	0	1
Risk Averse ($30-40 Reservation)	1,026	0.30	0.46	0	1
Risk Neutral ($50 Reservation)	1,026	0.29	0.45	0	1
Risk Loving ($60+ Reservation)	1,026	0.18	0.39	0	1
Max Observations	1,026				

3.4 How Well WholeTraveler Respondents Represent the Bay Area

Examining how the respondents who constitute our sample represent the entire San Francisco Bay Area population is important for understanding both the context that generates the following results and the resulting implications for interest in and adoption of the emerging transportation technologies and services among the broader regional population. Table 7 compares gender, education levels, and household income population shares for survey respondents with those for the nine Bay Area counties, a population-weighted regional average, and the entire U.S.

Education and income vary across the different samples. While 87% of the nationwide American Community Survey (ACS) sample reported at least a high school education, the WholeTraveler sample reported almost 97% at this level of education. The disparity is even greater for higher education: 30% of the U.S. population reported a college education or higher, but the values were 45% averaged across the Bay Area and 83% for the WholeTraveler sample. Similar trends occur in the income distribution, where only 11% of the nationally sampled households earned greater than $150,000 per year, compared with 24% averaged across Bay Area counties and 39% for the WholeTraveler sample.

Table 7. San Francisco Bay Area representation in WholeTraveler survey

	Female	**At Least HS Educ.**	**At Least Bachelor**	**HH Inc < $75K**	**HH Inc $75-150K**	**HH Inc $150-200K**	**HH Inc > $200K**
United States	50.8%	87.0%	30.3%	63.2%	25.7%	5.4%	5.7%
Bay Area Counties							
Alameda	51.0%	87.3%	43.9%	47.4%	29.6%	10.1%	12.9%
Contra Costa	51.2%	89.1%	40.3%	45.7%	28.1%	10.1%	13.6%
Marin	51.1%	93.1%	57.1%	39.2%	27.7%	10.8%	22.4%
Napa	50.3%	83.9%	33%	50.2%	30.7%	8.6%	10.5%
San Francisco	49.0%	87.4%	54.8%	44.5%	26.7%	10.4%	18.4%
San Mateo	50.8%	88.6%	47.1%	38.5%	30.6%	11%	20%
Santa Clara	49.9%	87.1%	49.1%	38.3%	29.7%	12.1%	19.9%
Solano	50.3%	87.5%	25.1%	53.5%	32.5%	7.9%	6.1%
Sonoma	51.0%	87.2%	33.1%	55.0%	29.8%	7.7%	7.4%

Pop. Weighted Bay Area	50.5%	87.8%	44.7%	47.6%	28.5%	9.4%	14.1%
WholeTraveler	**49.1%**	96.8%	82.6%	26.5%	34.1%	14.7%	24.7%
Female WholeTraveler Respondents	100%	98.4%	80.9%	31.5%	35.9%	13.3%	19.4%

This table compares population and demographic characteristics of the WholeTraveler Transportation Behavior Survey to the populations of nine San Francisco Bay Area counties. Population and demographic information for the counties are from the 2016 ACS.[14] Bold statistics indicate t-tests in which we fail to reject the null hypotheses that the WholeTraveler sample has the same mean value as the population-weighted ACS values at the 95% level.

One area of parity is the proportion of female respondents. In our survey, we obtained approximately even numbers of responses from male and female participants, paralleling the Bay Area population. In fact, the proportion of men who responded was not statistically significantly different than the proportion of women: we fail to reject the null hypothesis that 50% of our sample are female with 99.9% confidence for both the full cleaned sample of 1,026 respondents (confidence interval spans 43.8% to 54.2%) and the largest analyzed subsample of 826 (confidence interval from 43.5% to 55.0%). For female respondents only, education levels are comparable to the entire sample, and the income distribution exhibits less bias compared with the regional and national distributions. The percentage of respondents reporting household income above $200,000 annually falls from 25% to 19%, with the mass shifting almost entirely to incomes below $75,000.

The demographics observed in the WholeTraveler survey results are consistent with those of previous Bay Area transportation studies, which similarly obtained responses from a very highly educated and high-income group. The 2010–2012 California Household Travel Survey (CHTS) elicited responses from individuals with comparably high education levels (98% at least high school education, 73% at least a bachelor's degree, and 42% a graduate degree), albeit with a more representative income distribution (36% of respondents with household income below

[14] See https://www.census.gov/programs-surveys/acs/.

$75,000, 33% between $75,000 and $150,000, and 21% over $150,000) in a larger sample of 24,030 individuals from 9,719 households (Clewlow 2016). Surveys of City CarShare users and the 2015 California Millennials Dataset reveal similar patterns (Cervero and Tsai 2004; Alemi et al. 2018). Therefore, our sample (and in particular the sample of female respondents) reflects the samples from other regional studies.

4. Results: Adoption, Interest, and Regression Estimates

Here we first focus on the results of the WholeTraveler survey and discuss respondents' rates of adoption and interest in future adoption. Then, we present detailed results from our regression analysis.

4.1 Respondents' Current Adoption and Interest in Future Adoption

Respondents' stated adoption and interest results allow us to understand both the current technology penetration within our sample and the receptiveness to future adoption. Figure 2 reports the adoption and interest levels covering long-existing, accepted technologies through to more novel transportation modes and services. Interest in future adoption is stacked upon current adoption for each given technology, so each bar corresponds to the potential long-term market diffusion for that technology based on current engagement and perceptions.

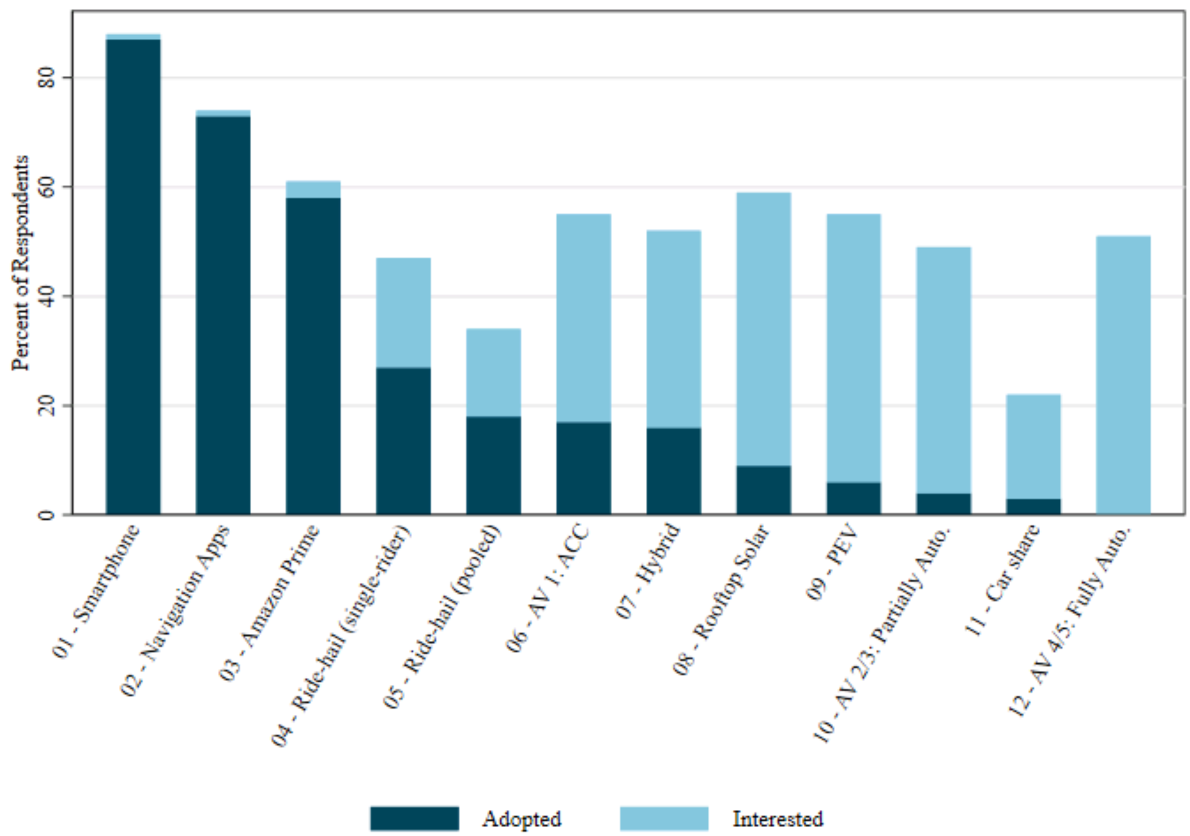

Figure 2: Adoption and interest in adopting by technology/service

Adoption and interest behavior for smartphones, navigation smartphone apps, and Amazon Prime memberships suggests these technologies and services have neared their saturation points within our sample. Respondents exhibit very high adoption rates, with roughly 90% of respondents in the sample owning a smartphone, 72% using navigation or trip-planning apps (e.g., Google Maps, Waze), and 58% having a membership to Amazon Prime. However, additional interest among those who have yet to adopt these technologies is limited. Only 1% of respondents are interested in purchasing a smartphone at a later point, while 3% are interested in starting to use navigation apps, and 6% are interested in adopting Amazon Prime.

Conversely, we observe generally low adoption but high interest for transportation technologies. Ride-hailing services (both single and pooled) exhibit the highest adoption rates (at

27% and 18%, respectively) among the transportation services. Both ride-hailing services receive similar levels of interest in future adoption: 27% express interest in adopting single-rider services, while 20% would consider using pooled ride-hailing. A mere 3% of respondents have adopted car-sharing services, while 19% of those sampled would be interested in eventually adopting car-sharing.

Among electrified vehicle technologies, hybrids (16% ownership rate) have been adopted at nearly three times the rate for PEVs (6%). However, interest in future adoption is higher for PEVs (53%) than for hybrids (42%).

Among AV technologies, ACC displays relatively high levels of adoption (17%). Although this is a new technology, the results suggest that this level of automation is either increasingly ubiquitous in many newer automobiles and/or there is a preference among respondents for vehicles with this technology. In addition, 4% of respondents reported having adopted partially automated vehicles. The list of currently available vehicles with partially automated technology in the level 2–3 range is small. Interest in future adoption of these technologies is strong and similar across all levels of automation: 46% of respondents interested in adopting ACC, 47% interested in partial automation, and a striking 51% of respondents in the sample are interested in adopting fully automated vehicles.

Although these results provide valuable insight into current rates of adoption and interest in future adoption, the regression analysis in the following subsections clarifies the drivers of and barriers to adoption, allowing better interpretation of these patterns. We present results by technology group. In Table 8, we report coefficient estimates for all variables we considered. The significant predictors identified in large part do not vary across model specifications when included in different combinations of variable sets (demographics, preference over mode attributes, and personality/risk preferences). Therefore, for the sake of brevity, in Tables 9 and 10 we only report the variables that show significance in the full model specification.

4.2 Predictors of Adoption and Interest, Shared Services

Table 8 shows our results for shared services including ride-hailing and car-sharing. The coefficient estimates represent percentage point differences relative to the omitted category. For example, a point estimate of 0.2 for those born in the 1980s regarding adoption of single passenger ride-hailing indicates that this age cohort is associated with a 20 percentage point marginal effect, or in other words is 20 percentage points more likely to have adopted this service relative to the omitted category (in this case, those born in the 1960s). In the following, we highlight what we consider to be the most important results of those presented in the table.

Younger generations are both more likely to have already adopted and to be interested in adopting ride-hailing services: those born in the 1980s and 1990s are 16–25 percentage points more likely to have adopted single-rider and pooled options for services like Uber or Lyft and are 10–14 percentage points more likely to express interest in future adoption of single-rider options than those born in the 1960s. On the other hand, relative youth is associated with somewhat less interest in car-sharing; those born in the 1970s and 1980s are 11–12 percentage points less likely to be interested in adopting car-sharing relative to those born in the 1960s.[15] Having a child under 8 years of age has a sizable and weakly significant negative impact on interest in adopting pooled ride-hailing services (9 percentage points less likely to be interested in adoption relative

[15] Although covariates such as age carry statistically significant coefficients in many cases, model adjusted R-squared values are generally low, suggesting many unobserved factors play key roles in determining technology and service choices. All models in Tables 8–10 have adjusted within R-squared values negligibly different than the overall adjusted R-squared value, suggesting they explain a similar amount of within-county variation as they do overall variation.

to those without young children); having a young child has no significant impact on current adoption.

High household income (being in the highest income quartile, above $200,000) is a strong predictor of single-rider ride-hailing adoption (18 percentage point marginal effect) and a weak predictor for car-sharing adoption (4 percentage point marginal effect) as compared to those with household incomes below $75,000. While adoption and interest do not significantly vary across income groups for pooled ride-hailing, a higher importance placed on predictable travel cost is associated with higher adoption rates for pooled ride-hailing (3 percentage point marginal effect).

Individuals who value minimizing environmental impact are slightly more likely to have already adopted ride-hailing services (2–5 percentage point increase for a one standard deviation increase in this score) and similarly more likely to be interested in adopting car-sharing services.[16] Other than age, and income in the case of single-rider ride-hailing, the strongest predictor of ride-hailing adoption is an extravert personality: a one standard deviation increase in Big Five extraversion (roughly 1 point) is associated with a 4 percentage point higher adoption rate for both single-rider and pooled ride-hailing options. Big Five agreeableness has a positive impact with a similar magnitude for pooled ride-hailing services as well.[17] While Big Five dimensions of personality play little role in informing current car-sharing adoption, future interest in car-sharing adoption is positively associated with agreeableness and openness and

[16] The variable Min. Env. Impact takes on values between -5 and 5. This variable has a standard deviation of 1.78. Therefore, an increase of one standard deviation in this variable is associated with a 2.2 percentage point increase in the adoption of pooled ride-hailing, and a 4.6 percentage point increase in the adoption of single-rider ride-hailing.

[17] BFI variables take values from 1 to 5 with a standard deviation close to 1. Therefore, the marginal effect (in percentage point) of a one standard deviation change is approximately equivalent to the coefficient estimate itself. However, the difference between someone scoring 1 versus 5 on a given BFI scale means a sizeable difference in adoption probability (i.e., 4*4 = 16 percentage point increase in likelihood of adoption for someone rating 1 on the extraversion or agreeableness scale versus someone rating 5).

negatively associated with conscientiousness. In our sample, risk preferences broadly do not predict adoption of or interest in ride-hailing or car-sharing, although risk-loving people have a 3 percentage point lower car-sharing adoption rate.

Table 8: Adoption and interest for shared services

	Adopted			Interested in Adopting		
	Ride-hail Single	Ride-hail Pooled	Car-Sharing	Ride-hail Single	Ride-hail Pooled	Car-Sharing
Demographic variables						
Born 1930s	0.1238	0.1106	0.0230	0.1478	-0.1638**	-0.1290
Born 1940s	-0.0730	-0.0580	0.0020	0.0920	-0.0925	-0.0563
Born 1950s	-0.0055	-0.0455	0.0122	-0.0218	-0.0552	-0.0098
Born 1970s	0.0622	-0.0023	-0.0009	-0.0048	0.0071	-0.1234***
Born 1980s	0.2001***	0.1615***	0.0172	0.1038*	0.0714	-0.1055**
Born 1990s	0.2515***	0.2305***	0.0390	0.1382*	0.0997	-0.0892
Any Child < 8yrs	-0.0526	-0.0605	0.0235	-0.0649	-0.0875*	0.0257
HH Income 75-150K	0.0341	0.0556	0.0161	0.0311	0.0085	0.0787**
HH Income 150-200K	0.0654	0.0562	0.0134	-0.0429	0.0086	0.0729
HH Income ≥ 200K	0.1833***	0.0198	0.0352*	0.0312	0.0011	0.0323
> 4yr College Ed.	0.0392	-0.0115	0.0163	0.0184	-0.0178	-0.0433
Female	0.0090	-0.0010	-0.0125	-0.0216	-0.0403	-0.0634**
Location-based variables						
Res. Pop. Density	0.0004	0.0024	0.0003	-0.0019	-0.0029*	0.0021
P.D. Pop. Density	-0.0007	0.0003	-0.0004	0.0000	0.0002	-0.0003
Res. Walk Score	0.0005	0.0007	0.0006**	0.0008	0.0016**	0.0008
Dist. to P.D. (10,20]	-0.0032	0.0050	-0.0046	0.1506***	0.0020	0.0036
Dist. to P.D. (20,50]	0.0252	-0.0314	0.0112	0.0503	-0.0675	-0.0467
Dist. to P.D. > 50mi	0.0574	0.0107	-0.0078	0.0363	0.0277	0.0108
Preference-over-mode-attribute variables						
Safety	0.0151	-0.0088	0.0049	-0.0033	-0.0077	0.0041
Low Cost	-0.0130	-0.0060	-0.0006	-0.0381*	0.0038	0.0041
Low Hassle	-0.0207	-0.0050	-0.0144*	0.0205	-0.0034	0.0013
Short Time	0.0102	-0.0073	0.0050	0.0445*	0.0103	0.0179
Predict. Time	0.0097	-0.0047	0.0077	-0.0089	-0.0028	-0.0460**
Predict. Cost	0.0076	0.0339***	-0.0000	-0.0007	-0.0029	0.0025
Multiple Stops	-0.0148	-0.0124	0.0035	0.0006	-0.0025	-0.0050
Min. Env. Impact	0.0260***	0.0124*	0.0011	-0.0018	0.0136*	0.0263***
Social Interaction	-0.0058	-0.0003	0.0010	-0.0086	-0.0080	0.0070
Personality and risk variables						
BFI Extraversion	0.0410**	0.0449***	0.0077	0.0252	0.0239	-0.0117
BFI Agreeableness	0.0210	0.0464**	-0.0029	-0.0062	0.0176	0.0356*
BFI Conscientiousness	-0.0143	0.0004	-0.0036	-0.0179	0.0090	-0.0355*
BFI Neuroticism	-0.0020	0.0024	-0.0061	-0.0138	0.0073	0.0033
BFI Openness	0.0151	-0.0028	0.0037	0.0116	-0.0185	0.0340**
Risk Averse ($1-20)	-0.0124	-0.0052	0.0006	-0.0752	-0.0480	-0.0013
Risk Averse ($30-40)	-0.0420	-0.0317	-0.0106	-0.0078	0.0365	0.0606
Risk Loving ($60+)	-0.0346	-0.0526	-0.0302**	-0.0051	-0.0468	-0.0283

Observations	826	826	826	587	675	804
Observations Y=1	239	151	22	170	145	167
Adjusted R^2	0.12	0.15	0.01	0.01	0.01	0.05

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated using a linear probability model and include all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3.3. The dependent variable = 1 in 'Adopted' models when the respondent regularly uses the tech/service. 'Interested in Adopting' utilizes the subsample that does not regularly use the technology and =1 when interested in future use of the service. Model results with t-stats, without $\mathbf{P'}_i$ variables, and using logistic regression are located in Appendix D in the supplementary materials.

4.3 Predictors of Adoption and Interest, Electrified Vehicle Technologies

Table 9 shows results for our electrified vehicle analyses, and we highlight some of the more noteworthy results below. Age mediates adoption of hybrids and PEVs in a meaningful way. Those born in the 1980s and 1990s are 6–9 percentage points less likely to have adopted hybrid or PEV technologies relative to those born in the 1960s, while those born in the 1950s have a 16 percentage point higher likelihood of currently owning a hybrid vehicle relative to the same comparison group. However, when it comes to interest in future adoption, those born in the 1980s are just as likely to be interested in adopting these technologies, and those born in the 1990s are 19 percentage points more likely to be interested in adopting hybrid vehicles than the comparison group. When only demographic and location regressors are included, those born in the 1980s and 1990s are significantly more likely to be interested in adopting PEVs (11–12 percentage points) relative to the omitted category (see Appendix Table D5 in the supplementary materials). This suggests that younger generations are significantly more interested in future PEV adoption than the omitted category, but age is correlated with some of the mode attribute, personality, and risk preference measures included in the primary specification reported here. The only exception to this general trend is that those born in the 1940s appear to have a particularly high interest in adopting PEVs (14 percentage points more likely to be interested than those born in the 1960s).

Higher incomes are monotonically associated with adoption of electrified vehicle technologies, with a roughly 3–5 percentage point step-up increased adoption likelihood when moving between the second, third, and fourth income quartiles. In total, households earning above $200,000 are 13 and 7 percentage points more likely to adopt hybrids and PEVs, respectively, than are households earning under $75,000. There is no significant difference across income groups with respect to interest in adopting PEVs, and the two highest income quartiles are 12–16 percentage points less likely to be interested in adopting hybrids. This suggests that PEVs are roughly equally appealing across income groups, even if those with lower incomes are not yet able to adopt. On the other hand, hybrids appear less compelling to those with higher incomes when they consider future adoption.

Education beyond a bachelor's degree, a factor positively correlated with income, is positively associated with current adoption of hybrids (9 percentage points) and interest in adopting PEVs (10 percentage points). Identifying as female is associated with a 10 percentage point decreased likelihood of interest in future adoption of PEVs, an effect not seen for the more established hybrid vehicle technology. Population density in the census block group of the primary destination is negatively associated with adoption of hybrid vehicles, which conversely suggests that hybrids are relatively more popular in less densely populated areas.

High levels of both risk aversion and risk loving weakly predict a small decreased likelihood of current PEV adoption relative to risk-neutral respondents. In addition, risk-loving preferences are associated with decreased interest in future adoption of both electrified vehicle technologies (-14 percentage points for hybrids and -16 percentage points for PEVs), suggesting either that risk-loving individuals view these technologies as proven and ordinary, or they are drawn toward vehicle characteristics and appearances not typically found in hybrids or PEVs.

Those placing high importance on low travel cost are 3 percentage points more likely to adopt PEVs, while high regard for low hassle and predictable costs decreases PEV adoption rates (approximately 2 percentage points). Those placing high value on minimizing environmental impact are more likely to be interested in both technologies. Finally, a higher Big Five conscientiousness score is negatively associated with current adoption of both electrified vehicle technologies and interest in future adoption of PEVs (-3 percentage points for a one standard deviation increase), and a one standard deviation increase in agreeableness is associated with a 7 percentage point increase in interest in PEV adoption.

Finally, commute distance does not appear to be an obstacle to adoption of PEVs for most survey respondents. Strong evidence of commute "range anxiety" would manifest itself as statistically significant, negative effects on all three bins of commute distance, growing in magnitude as the commute distance lengthened. We do not observe such a pattern; instead we find that living more than 50 miles away from one's primary commute destination yields no effect on current adoption statistically distinguishable from zero. The only statistically significant effect found for commute distance is an 8 percentage point increased likelihood of interest in adopting PEVs for those in the 10–20 mile bin relative to those less than 10 miles from their destination. However, this interpretation may need to be tempered by the recognition that the PEV technology category could include responses associated with PHEVs, because this category was not separately defined. It would be expected that PHEVs are associated with less range anxiety than BEVs.

Table 9: Adoption and interest for electrified vehicle technologies

	Adopted		Interested in Adopting	
	Hybrid	PEV	Hybrid	PEV
Demographic variables				
Born 1940s	0.0576	0.0078	-0.0557	0.1440*
Born 1950s	0.1626***	-0.0259	0.0475	0.1028
Born 1980s	-0.0940**	-0.0835***	0.0400	0.0614
Born 1990s	-0.0803*	-0.0644**	0.1880***	0.0792
Any Children < 8yrs	-0.0037	0.0569*	-0.0103	-0.0164
HH Income [75K,150K)	0.0545*	-0.0002	0.0213	0.0332
HH Income [150K,200K)	0.0841**	0.0467*	-0.1216*	0.0820
HH Income ≥ 200K	0.1316***	0.0740**	-0.1583***	0.0928
> 4yr College Ed.	0.0933***	0.0298	0.0241	0.0974**
Female	0.0382	-0.0102	0.0334	-0.0985**
Location-based variables				
P.D. Pop. Density	-0.0015*	-0.0003	-0.0021	-0.0020
Dist. to P.D. (10,20]	0.0081	0.0325	0.0099	0.0779*
Preference-over-mode-attribute variables				
Low Cost	0.0036	0.0261***	0.0130	0.0063
Low Hassle	0.0185	-0.0236**	0.0149	0.0137
Short Time	-0.0209	0.0047	0.0414*	0.0412*
Predict. Cost	0.0066	-0.0208**	-0.0423**	-0.0281
Multiple Stops	-0.0071	0.0032	-0.0198	-0.0352***
Min. Env. Impact	-0.0012	0.0055	0.0192*	0.0368***
Personality and risk variables				
BFI Extraversion	-0.0048	-0.0116	-0.0418**	0.0052
BFI Agreeableness	0.0220	0.0096	0.0240	0.0652**
BFI Conscientiousness	-0.0325**	-0.0408***	0.0390	-0.0453*
Risk Averse ($1-20)	0.0026	-0.0421*	-0.0899*	-0.0772
Risk Loving ($60+)	0.0394	-0.0467*	-0.1400**	-0.1561***
Observations	826	826	699	772
Observations Y=1	127	54	306	426
Adjusted R^2	0.07	0.06	0.05	0.07

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated using a linear probability model and have all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3.3. The dependent variable = 1 in 'Adopted' models when the respondent owns the technology. 'Interested in Adopting' utilizes the subsample that does not own the technology and =1 when interested in future ownership. Constant and coefficients for variables that do not appear statistically significant in any of the models presented in this table (Born 1930s; Born 1970s; Res. Pop. Density; Res. Walk Score; Dist. to P.D. 20-50mi, Dist. to P.D. >50mi; Risk Averse ($30-40); Safety; Predict. Time; Social Interaction; BFI Neuroticism; BFI Openness) are not reported in this table, but are reported in Appendix D in the supplementary material. Model results with t-stats, without $\mathbf{P'}_i$ variables, and using logistic regression are located in Appendix D in the supplementary material.

4.4 Automated Vehicle Technologies

Table 10 shows results for our AV analysis, and selected results are discussed in the following.[18] Younger respondents are more likely to express interest in the relatively more advanced AV technologies: those born in the 1990s have a 22–23 percentage point increased interest in adoption for either partially or fully automated AVs relative to those born in the 1960s. Being born in the 1950s is negatively associated with current adoption of ACC (-10 percentage points relative to those born in the 1960s), although being born in the 1940s is positively associated with adoption interest for partially automated technologies (22 percentage points). Female identification is negatively associated with current adoption of partially automated technologies (-3 percentage points) and interest in future adoption of all automation levels (-16 percentage points for ACC and partial automation, -26 percentage points for full automation).

As expected, these results also highlight the importance of income as a driver for adoption of technologies with a high upfront cost. Income above $200,000 is a strong positive predictor of ownership of a vehicle with either ACC (11 percentage points) or partially automated (4 percentage points) technology. Newer cars are more likely to have these technologies, so this finding may reflect the ability to buy recent model vehicles. Additionally, high household incomes continue to serve as a signal of adoption interest: belonging to the second-highest income quartile confers a 12 percentage point higher interest in fully automated AVs relative to those in the lowest income quartile, while membership in the highest income quartile yields an 11–19 percentage point higher interest in any of the AV technologies.

Finally, individual personality and risk preferences play a role in adoption and interest in future adoption of AV technologies. A one standard deviation increase in the Big Five

[18] Fully automated vehicle technology is not included in models of adoption, because this technology is not currently available in the market.

agreeableness personality dimension is associated with a roughly 3 percentage point higher adoption rate for ACC, while risk lovers exhibit a 13 percentage point greater likelihood of ACC adoption relative to risk-neutral respondents. Focusing on those who are not current adopters, adoption interest is significantly higher for those expressing risk-neutral preferences. Extreme risk aversion is correlated with 12–15 percentage point lower interest in partially and fully automated vehicles, whereas moderate risk aversion is correlated with 10–11 percentage point lower interest in partial automation and ACC. Similarly, risk-loving respondents exhibit interest in all levels of automation that is 10–14 percentage points lower than the interest of risk-neutral individuals who have not yet adopted.[19]

Table 10: Adoption and interest for AV technologies

	Adopted		Interested in Adopting		
	ACC	Partially Autom-ated	ACC	Partially Autom-ated	Fully Autom-ated
Demographic variables					
Born 1940s	0.0271	0.0269	0.0698	0.2159***	0.0491
Born 1950s	-0.0960**	-0.0300	0.0647	0.0615	0.0076
Born 1990s	-0.0706	-0.0115	0.1043	0.2218***	0.2297***
HH Income [75K,150K)	0.0427	0.0089	0.0487	0.0686	0.1083**
HH Income [150K,200K)	0.0513	0.0024	0.1128*	0.0567	0.1186**
HH Income ≥ 200K	0.1131***	0.0434**	0.1115*	0.1502***	0.1934***
Female	-0.0070	-0.0273*	-0.1576***	-0.1579***	-0.2600***
Preference-over-mode-attribute variables					
Min. Env. Impact	-0.0242***	-0.0122**	0.0188	0.0203*	0.0072
Social Interaction	0.0019	0.0012	-0.0168**	-0.0038	-0.0024
Personality and risk variables					
BFI Agreeableness	0.0448**	0.0048	-0.0017	0.0057	0.0095
Risk Averse ($1-20)	-0.0471	-0.0232	-0.0628	-0.1470***	-0.1218**
Risk Averse ($30-40)	-0.0093	-0.0295	-0.1060**	-0.1003**	-0.0538
Risk Loving ($60+)	0.1254***	0.0065	-0.1198*	-0.1002*	-0.1405***
Observations	826	826	688	793	823
Observations Y=1	138	33	329	384	438

19 The high relative interest among risk-neutral respondents may be due in part to strong correlations with high levels of both education and income within the subsample: 34% of risk-neutral respondents have household incomes above $200,000, while 85% have at least a bachelor's degree and 46% additional education beyond a bachelor's.

Adjusted R^2	0.04	0.01	0.03	0.06	0.11

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ report statistical significance for robust standard errors. Results were generated using a linear probability model and have all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3.3. The dependent variable = 1 in 'Adopted' models when the respondent owns the technology. 'Interested in Adopting' utilizes the subsample that does not own the technology and =1 when interested in future ownership. Constant and coefficients for variables that do not appear statistically significant in any of the models presented in this table (Born 1930s; Born 1970s; Born 1980s; Any Children < 8 yrs; > 4yr College Ed.; Res. Pop. Density; P.D. Pop. Density; Res. Walk Score; Dist. to P.D. 10-20mi; Dist. to P.D. 20-50mi; Dist. to P.D. >50mi; Safety; Low Cost; Low Hassle; Short Time; Predict. Time; Predict. Cost; Multiple Stops; BFI Extraversion; BFI Conscientiousness; BFI Neuroticism; BFI Openness) are not reported in this table, but are reported in Appendix D in the supplementary material. Model results with t-stats, without $\mathbf{P'}_i$ variables, and using logistic regression are located in Appendix D in the supplementary material.

5. Takeaways for Adoption and Interest

Key finding 1: **Although higher-income people are disproportionately represented among current adopters of most new technologies, low- to middle-income people are just as likely to have adopted *pooled* ride-hailing.** Previous studies have found that electrified (Caperello and Kurani 2011; Langbroek et al. 2017; Nayum et al. 2016) and automated (Fortune.com 2018; Investopedia.com 2018) vehicle technologies as well as ride-hailing use (Alemi et al. 2018; Dias et al. 2017; Smith 2016) all tend to be associated with relatively higher incomes. In contrast, while our study confirms that those in the highest income group are significantly more likely to have adopted almost all of the analyzed technologies and services, we find one important exception: pooled ride-hailing. We find that all income groups are similarly likely to have adopted or be interested in adopting pooled ride-hailing. Ride-hailing does not include high upfront costs, as many other options do, and pooled ride-hailing costs less than single-rider ride-hailing. Shared pool service may therefore help lower- and middle-income people by giving them more flexibility and making it easier for them to engage in and access the benefits of these emerging transportation technologies and services.

Key finding 2: **The gap between current adoption and future adoption interest suggests younger generations have the potential to fuel automated and electrified vehicle market penetration, just as they are currently fueling ride-hailing uptake, if given the means to do so.** Those born in the 1980s and 1990s are 16–25 percentage points more likely to have already adopted either single-rider or pooled ride-hailing services in comparison to those born in the 1960s. Average adoption of single and pooled ride-hailing for those born in the 1960s is 21% and 12%, respectively. Therefore, those born in the 1980s and 1990s are about twice as likely or more to have adopted ride-hailing than the omitted category. This result is consistent with past research (Alemi et al. 2018; Clewlow and Mishra 2017; Dias et al. 2017; Kooti et al. 2017; Smith 2016). However, we find that, while these cohorts exhibit 6-9 percentage point lower current adoption rates for electrified vehicles, they are just as likely or more likely to be interested in future adoption of electrified vehicle technologies relative to older generations. This indicates that future interest in electrified technologies is not as highly concentrated in older generations as has been found with regard to current ownership (e.g., Langbroek et al. 2017). In addition, those born in the 1990s exhibit rates of interest in future adoption of higher levels of automation that are 22–23 percentage points higher than exhibited by those born in the 1960s. Consistent with the mixed findings on age shown in other studies of AV technologies (Abraham et al. 2016; Haboucha et al. 2017; Bansal and Kockelman 2018), we show this strong effect associated with interest in adoption by the youngest cohorts in the study, but also relatively higher interest in PEV and partially automated vehicle technologies associated with being born in the 1940s relative to the 1960s.

Key finding 3: **A longer commute does not appear to be a barrier for high interest in PEV adoption.** Those with daily commutes of greater than 10 miles are as likely to have adopted PEVs, and are 8 percentage points more likely (in the case of those with commutes between 10 and 20 miles) to be interested in future adoption of PEVs, compared with those who have commutes of less than 10 miles. This is perhaps because a longer commute could provide a faster return on investment via greater fuel-cost savings. At the same time, the fixed nature of commuting distances may mitigate what is traditionally thought of as "range anxiety" (Franke et al. 2012; Neubauer and Wood 2014), even if the commute is relatively long, since PEV ranges may already be seen as sufficient to satisfy the needs of many Bay Area commuters. However, this interpretation may need to be tempered by the recognition that the PEV technology category could include responses associated with PHEVs, because this category was not separately defined within the survey. PHEVs would likely be associated with less range anxiety than BEVs, which might be contributing to this result.

Key finding 4: **Women are less likely to adopt and/or be interested in adopting most new transportation technologies, with the exception of ride-hailing.** In particular, women are 3 percentage points less likely to have adopted partially automated vehicles, 16–26 percentage points less likely to be interested in adopting vehicles with any level of automation, 10 percentage points less likely to be interested in adopting PEVs, and 6 percentage points less likely to be interested in adopting car-sharing. Similar patterns have been found in other studies as well (Langbroek et al. 2017; Plötz et al. 2014; Payre 2014; Investopedia.com 2018). On the other hand, we find that female identification is associated with no significant difference in current use of or future interest in ride-hailing. This finding is consistent with Smith (2016), whereas Alemi et al. (2018) and Kooti et al. (2017) both found that women were actually more likely to use ride-hailing services. In any case, designing and/or promoting emerging transportation technologies to cater to women's needs and wants could increase market potential and substantially impact overall transportation energy use. Ride-hailing may provide an opportunity to better understand what types of transportation innovations are more appealing to women.

Key finding 5: Much about transportation technology adoption remains to be explained. Although we include many explanatory variables—particularly those associated with mode attribute preferences, personality, and risk characteristics in addition to the more traditional demographic and locational regressors—our variables only explain around 5%–15% of adoption (based on adjusted R-squared values). Our results help identify important characteristics that inform our understanding of adoption, and the results are sometimes consistent with and sometimes contradict previous findings. For example, in contrast to what we might expect based on previous studies (Skippon and Garwood 2011), we find that PEV ownership is not positively correlated with agreeableness and openness, and is significantly negatively associated with conscientiousness. Also in contrast to previous findings (Haboucha et al. 2017), we find that current adoption of AV technologies tends to be negatively correlated with wanting to minimize environmental damage, although the result for future adoption interest becomes less clear. On the other hand, we find results somewhat consistent with Hulse et al. (2018) in that risk-loving individuals seem relatively uniformly uninterested in all three levels of automation relative to risk-neutral individuals, but risk-loving preferences are positively associated with current ACC adoption. The fact that both risk-averse and risk-loving individuals tend to be less interested in future adoption of all AV technologies relative to risk-neutral individuals is a novel and interesting finding, but it poses more questions than it answers. All of this suggests that additional analysis is necessary. For example, because many characteristics are related (e.g., age and income), cluster analysis can combine these to identify similar types of people who may have similar adoption patterns. Conversely, such characteristics may need to be further separated through interactions. For example, openness to new technology may be moderated by age or risk preferences. We intend to explore these topics in future research.

6. Conclusions

The transportation technologies and services we examine have great potential to change future energy use and sustainable mobility patterns. The impact of these technologies will depend largely on their adoption by users in key geographies. The results of our analysis provide information about the characteristics of current users as well as the potential drivers of adoption. These insights contribute to ongoing efforts to plan the efficient transportation systems of the future.

The relative value of some new transportation technologies may be driving adoption already. For example, low- to middle-income people may benefit from pooled ride-hailing options just as much as higher-income people, and people with long commutes may benefit from the low per-mile cost of PEVs. Our results also suggest that market penetration may be increased by helping already-interested groups access the resources necessary for adoption; in particular, young people demonstrate great interest in AV technologies and are just as interested as most older generations in adopting PEVs but are much less likely to have already done so, which suggests they may need additional resources to enable them to move to adoption. In addition, women represent a large potential driver of market expansion for new transportation technologies. Although women are currently less likely to adopt or be interested in adopting PEV and AV technologies, designing or marketing these technologies with women's preferences in mind might help overcome this inequality. Insights might be gained from ride-hailing adoption patterns, as women appear to be just as open to ride-hailing services in our sample as men.

While our study is specific in its geographic scope (the San Francisco Bay Area) and has disproportionately high education and income of respondents even within the Bay Area, we feel it can provide valuable insights into transportation development in other regions as well. The analysis of associations reflected in this survey should reflect many urban environments where these technologies are well developed. The results should be carefully examined for applicability when used in new contexts.

In future research, we will analyze the survey results in more depth and address other themes related to new transportation technologies. Specific approaches will include factor analysis that defines groups of people with similar characteristics to attempt to eliminate the correlation between our variables, and factorial interaction analysis to separate characteristics into smaller groups of people. We will also delve deeper into the effects of having children on transportation choices, estimate how future price reductions may impact ride-hailing, and examine whether ride-hailing replaces public transit use or enables it by facilitating access to public transit hubs.

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Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area - APPENDICES

Appendix A: WholeTraveler Transportation Behavior Study Background

This research is a part of the WholeTraveler Transportation Behavior Study. This study is a part of the U.S. Department of Energy's (DOE) Energy Efficient Mobility Systems (EEMS) program. This program envisions an affordable, efficient, safe, and accessible transportation future in which mobility is decoupled from energy consumption. The EEMS Program conducts early-stage research and development at the vehicle, traveler, and system levels, creating new knowledge, tools, insights, and technology solutions that increase mobility energy productivity for individuals and businesses.

The SMART Mobility Consortium (Consortium) is a multi-year, multi-laboratory collaborative dedicated to further understanding the energy implications and opportunities of advanced mobility solutions. The Consortium is the EEMS Program's primary effort to create tools and generate knowledge about how future mobility systems may evolve and identify ways to reduce their energy intensity. It also identifies research and development gaps that the EEMS Program may address through its advanced research portfolio and generate insights that will be shared with mobility stakeholders. The Consortium consists of five focused pillars of research; Connected and Automated Vehicles, Mobility Decision Science, Multi-Modal Transport, Urban Science, and Advanced Fueling Infrastructure. This research was developed as part of the Mobility Decision Science Pillar that aims to identify the transportation energy impacts of potential travel and lifestyle decisions and understand the human role in the mobility system.

National (e.g., the U.S. National Household Travel Survey) and regional (e.g., California Household Travel Survey) travel surveys have well-acknowledged limitations with respect to documenting consumer acceptance of emerging transportation technologies, but in the absence of access to propriety data, surveys are often the only option to study questions of interest. Primary among these limitations is the fact that their geographic scope tends to include areas across which emerging technologies do not have a consistent presence. A secondary limitation is that they tend to provide a static snapshot of current user demand and/or expected demand for transportation technologies, which frequently update their consumer-facing attributes as business models change; more longitudinally-oriented research designs are likely to have higher utility for researchers interested in the energy impacts of emerging transportation technologies. In coping with these and other data inadequacies, simulation models tend to rely on heuristics of consumer demand or other behavioral parameters.

The WholeTraveler survey grapples with the same challenges faced by other travel surveys, but confronts this challenge of assessing consumer demand for technologies with rapidly changing attributes in a novel fashion. Rather than rely on being able to resurvey participants or capture the before/after of adoption and/or usage behavior through a longitudinal structure – both of which apply to the contrast between people's current and future travel decisions – the WholeTraveler survey instead focuses on the contrast between people's current and past travel decisions. It does this by incorporating a "life-history" calendar, in which respondents reflect on the periods in their lives at which they made choices to use different transportation modes. Such calendars have been used in several recent transportation behavior studies, particularly in Europe and Japan (e.g., Beige and Axhausen 2012; Oakil et al. 2014; Schoenduwe et al. 2015; Zhang, Yu and Chikaraishi 2014), but not yet in the United States, to our knowledge. The WholeTraveler survey further distinguishes itself with respect to its treatment of time by focusing on people's formative influences, which research suggests can significantly influence transportation behavior later in life (Smart and Klein 2017). As different strata of the population of any given geographic area are undergoing similar life events at any given time, these life-history and formative influence data should provide insights into market segmentation for certain emerging transportation technologies (e.g., the relatively higher value for reliable transportation options for families with young children). In addition, the WholeTraveler survey collects data on formative influences including personality traits, as laid out in the Big Five Inventory (Rammstedt and John 2007), and consumer risk and time preferences, as revealed by the Certainty Equivalent and Multiple Price list approach used in many studies (e.g., Bostic et al. 1990; Holt and Laury 2002; Plott and Zeiler 2005; Andersen et al. 2008; Harrison and Ruström 2008; and Meier and Sprenger 2009).

The overarching objective of the WholeTraveler Transportation Behavior Study is to understand travel choice patterns, preferences, and decision-making processes with the advent of new mobility technologies. In addition, an aim is to understand how these patterns interrelate with multiple dimensions of heterogeneity across the population. The WholeTraveler Transportation Behavior Study implements a two-phased survey of the transportation behaviors, attitudes, and preferences with a focus on the San Francisco Bay Area region.

Phase 1 of the survey is the source of data for this analysis. It consisted of a web-based survey with questions related to: (1) demographic and household characteristics; (2) formative influences, which research suggests can significantly influence transportation behavior later in life (Smart and Klein 2017); (3) personality traits and individual characteristics, including the Big Five Inventory 10 (Rammstedt and John 2007), and elicitation of risk and time preferences, based on the Certainty Equivalent and Multiple Price list approach used in many studies (e.g., Bostic et al. 1990; Holt and Laury 2002; Plott and Zeiler 2005; Andersen et al. 2008; Harrison and Ruström 2008; and Meier and Sprenger 2009); (4) a "Life History Calendar," which identifies an individual's significant life changes and patterns of transportation mode use over time and has been used in several recent transportation behavior studies in Europe and Japan (e.g., Beige and Axhausen 2012; Oakil et al. 2014; Schoenduwe et al. 2015; Zhang, Yu and Chikaraishi 2014); and (5) current transportation needs, constraints, and choices, including commute distance, routing options, car ownership, transportation mode use, e-commerce/home delivery behavior, and awareness and use of new mobility technologies and services.

Participants were offered the option to enroll in Phase 2 of the survey after they completed Phase 1. Phase 2 involved voluntary collection of one week's worth of Google Location History GPS time stamped data. Completion of Phase 2 was reimbursed with an additional $20 Amazon gift card.

Appendix B: SAE Levels of Automation

The following definitions were taken directly from the American National Standards Institute (ANSI) blog entitled "SEA Levels of Driving Automation," which does a nice job of summarizing the relevant context, and can be accessed here: https://blog.ansi.org/?p=158517.

- Level 0 – No Driving Automation
  - The performance by the driver of the entire dynamic driving task (DDT). Basically, systems under this level are found in conventional automobiles.
- Level 1 – Driver Assistance
  - A driving automation system characterized by the sustained and operational design domain (ODD)-specific execution of either the lateral or the longitudinal vehicle motion control subtask of the DDT. Level 1 does not include the

execution of these subtasks simultaneously. It is also expected that the driver performs the remainder of the DDT.

- Level 2 – Partial Driving Automation
  - Similar to Level 1, but characterized by both the lateral and longitudinal vehicle motion control subtasks of the DDT with the expectation that the driver completes the object and event detection and response (OEDR) subtask and supervises the driving automation system.
- Level 3 – Conditional Driving Automation
  - The sustained and ODD-specific performance by an automated driving system (ADS) of the entire DDT, with the expectation that the human driver will be ready to respond to a request to intervene when issued by the ADS.
- Level 4 – High Driving Automation
  - Sustained and ODD-specific ADS performance of the entire DDT is carried out without any expectation that a user will respond to a request to intervene.
- Level 5 – Full Driving Automation
  - Sustained and unconditional performance by an ADS of the entire DDT without any expectation that a user will respond to a request to intervene. Please note that this performance, since it has no conditions to function, is not ODD-specific.

Appendix C: WholeTraveler Phase 1 Survey Instrument

Any notes in this light blue italic font below are descriptions of the survey design and function only and are not visible to survey respondents.

WHOLETRAVELER TRANSPORTATION BEHAVIOR STUDY

PURPOSE AND BACKGROUND

You are being asked to participate in a research study lead by Anna Spurlock, PhD at Lawrence Berkeley National Laboratory (LBNL). The Department of Energy (DOE) sponsors this study. It is a part of the DOE SMART (Systems and Modeling for Accelerated Research in Transportation) Mobility Initiative.

The purpose of the WholeTraveler study is to learn about four main topics. First, what types of transportation options people living in the Bay Area are using. Second, why those choices may change over time. Third, opinions about newer technologies like electric vehicles, apps like Uber and Lyft, online shopping, and self-driving cars. Finally, how significant life circumstances (moving, finishing school, living with a partner or spouse, having children, etc.) and personality characteristics relate to preferences for different transportation options. This information will be used to improve transportation system models. It may also inform policies to improve transportation system efficiency.

PROCEDURES: If you agree to be in this study, the following will happen:

The study happens in two phases. You are invited to take part in both. Both phases are entirely voluntary. However, if you do not complete Phase 1 you cannot participate in Phase 2.

Phase 1: The first phase is an online survey. If you choose to participate you will answer questions about: your transportation decisions, your life history, and some other characteristics. The survey will take about 20 minutes to complete. You may stop part way through and return to complete the survey at any time. Resource Systems Group, INC (RSG) is running the online survey for LBNL. RSG is very experienced in transportation survey research.

Phase 2: If you complete the online survey you will be offered the option to join the second phase of the study. In the second phase you will follow some simple steps to provide a week's worth of your GPS location data. Google collects these data using your smartphone while you go about your normal day-to-day activities. These Google Location History data are collected through any Google smartphone apps linked to your Google Account (such as Google Maps). The research team will not have direct access to your smartphone in any way. First, you will follow simple set-up steps. Then at the end of a week you will download a single file with your data, confirm the date range of data you are willing to submit, and upload the data. You will also be asked to answer a short set of questions about the transportation options you used during the selected week. All told, this will take 10-30 minutes.

PARTICIPANT REQUIREMENTS

You must be a San Francisco Bay Area resident to participate. In addition you must be 18 years or older. To respond to the Phase 1 online survey you must have Internet access and be able to use a laptop or desktop computer. If you choose to participate in Phase 2 of the study, you must additionally have an iOS or Android smartphone that you do not share with any other individual. Finally, you must either have or be willing to obtain a Google Account and have the Google Maps app installed on your smartphone.

RISKS/DISCOMFORTS

If you take the online survey, your survey responses will be linked to your residential address. Because of this there is a risk that your identity could be linked to the information you provide. If you choose to take part in the second phase of the study there could be additional risks. In particular, through your GPS location data your common destinations, transportation patterns, or daily schedule could be observed. The primary risk to you would be unauthorized access to your data. There may also be other risks that we cannot predict.

Steps will be taken to ensure data security in order to minimize these risks. Data transfer and storage will follow industry best practices for security. In addition, access to the survey and GPS location-linked data will be highly controlled. An LBNL cyber security specialist has approved all data transfer, storage and access protocols.

BENEFITS

We do not anticipate that you will experience any direct benefits from taking part in the study other than the incentive payments described below. There is a potential benefit to society. In particular, the information we collect may inform policies to improve transportation system efficiency.

FINANCIAL CONSIDERATIONS

If you complete the Phase 1 online survey you will receive a $10 payment in the form of an Amazon Gift Card. The gift card will be emailed to you. If there are questions in the survey that you do not want to answer you may skip them. However, if you do not answer any required questions marked with an asterisk (*) you will not receive the payment.

If you submit one week's worth of Google Location History data for the second phase of the study, you will receive an additional $20 payment. This payment will also be in the form of an emailed Amazon Gift Card.

There will be no cost to you to participate in this study.

CONFIDENTIALITY

We will do everything we can to keep information about you protected. Any of the location-linked data you provide to us will only be accessible by authorized personnel. These data will only be transferred using encrypted secure methods. These data will be stored on a dedicated secure server at LBNL. These original address- and location-linked data will only be maintained for use in this study. Addresses, email addresses, and other location data will be deleted once the study is completed.

A de-identified version of the dataset will be shared with other researchers contributing to the SMART Mobility Initiative. This de-identified version will be stripped of all email address, residential address, common destination, and GPS location information so that all survey responses are anonymous. It will include the Census Block Group associated with: your residential address, any common destinations you indicate in the survey, and any GPS locations in the data from Phase 2. A Census Block Group is a geographic area that generally includes between 600 to 3000 residents. Unaltered responses to all other questions will be included in the de-identified version of the data. This de-identified version of the data will be made publicly available through the Transportation Secure Data Center (TSDC) at the National Renewable Energy Laboratory. You can find out more about the TSDC here: : https://www.nrel.gov/transportation/secure-transportation-data.html.

Results from analyses of the data may be published, but only in aggregated form. Your individual data will not be published.

If you participate in Phase 2 of this study and choose to provide your Google Location History data, be aware that Google collects those data and uses them for their own purposes. Google does not share those data with any companies, organizations or individuals outside of Google except under specific circumstances (with consent, with domain administrators, for external processing, or for legal reasons). While you need to allow Google to store your Location History over the course of a week if you want to participate in Phase 2 of this study, you can delete your Location History in-part or entirely, and turn off the preferences allowing Google to access or store your location, at any time. We will provide you with instructions for how to do this after completing Phase 2. More information about Google's privacy policy can be found here: :
https://static.googleusercontent.com/media/www.google.com/en//intl/en/policies/privacy/google_privacy_policy_en.pdf.

QUESTIONS

Any further questions you have about taking part in this study will be answered by:

Dr. Anna Spurlock at (510) 495-2072 or wholetraveler@lbl.gov.

Any questions you have about technical aspects of the Phase 1 online survey (login, website, or technical difficulty responding to any of the questions) will be answered by:

Resource Systems Group, INC (RSG) at wholetraveler@rsginc.com.

Any questions you have about your rights as a research subject will be answered by:

Lawrence Berkeley Lab Human Subjects Committee at (510) 486-5399

PARTICIPATION IN RESEARCH IS VOLUNTARY

You have the right to not take part in this study or to stop taking part at any time. If you would like a copy of this consent form to keep, you can print it out now, or access it at wholetraveler.lbl.gov at any time that is convenient. If you wish to participate, you should click "Start the Survey," below

AUTHORIZATION

I understand that by clicking "Start the Survey," below I am stating that: I have read this consent form; all of the questions I asked have been answered to my satisfaction; and I volunteer to participate in this research. I understand that my participation signifies consent for the researchers to use any data I provide as described above.

If you were given a password for this survey, please enter it below and click the "Start the Survey" button...

e.g., password123

Start the Survey

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Welcome to the WholeTraveler Transportation Behavior Study online survey. The survey has four sections. Throughout this survey, please use the following definitions for the terms “Household” and “Vehicle”:

- **Household:** people you live with and regularly coordinate transportation with (e.g., carpooling, purchasing/sharing a car, planning commute schedule).
- **Vehicle:** car, truck, SUV, van, or other passenger vehicle. Motorcycles or electric bicycles are not considered vehicles for the purposes of this survey.

Required questions are indicated with an asterisk “*”.

Please click "Next" to begin.

Next »

Questions or comments? Contact us at wholetraveler@rsginc.com

5%

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Section 1: In this section we will ask you questions about your current transportation needs and choices.

Please click "Next" to continue.

« Previous | Next »

Questions or comments? Contact us at wholetraveler@rsginc.com

7%

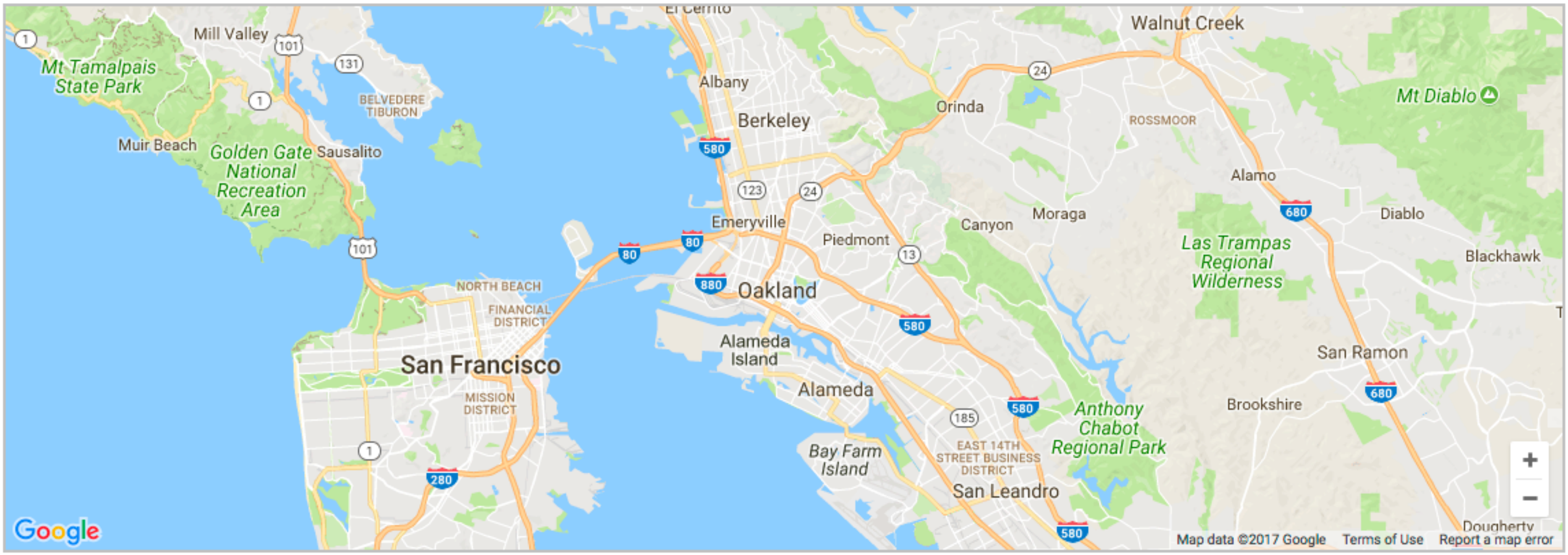
QUESTION 1.1 (*Survey will not proceed unless they answer)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Enter the address or cross streets of the place you commute to outside your home the most frequently in your typical day-to-day activities. We will refer to this as your "primary destination" for the remainder of this survey.

You can also double-click to zoom in on the map to select a location.

Enter a location or address



« Previous

Questions or comments? Contact us at wholetraveler@rsginc.com

10%

Address selected as demonstration in this document: 1 Cyclotron Rd, Berkeley, CA 94720, USA
References to this address hereafter show how the address a respondent enters will be referenced further in the survey.

*QUESTION 1.2   (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*How many days per week on average do you go to your primary destination, **1 Cyclotron Rd, Berkeley, CA 94720, USA**?

Please select...

Dropdown options:
0 days
1 day
2 days
3 days
4 days
5 days
6 days
7 days

*Which of the following options best describes your primary destination, **1 Cyclotron Rd, Berkeley, CA 94720, USA**?

Please select all that apply.

- ☐ My work
- ☐ My school
- ☐ The work or school of a household member
- ☐ Other Please specify...

« Previous | Next »

Questions or comments? Contact us at wholetraveler@rsginc.com

12%

*QUESTION 1.3 (*Survey will not proceed unless they answer - though they can answer nothing for the "Other" row and still proceed)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Please indicate the **last time you used** each of the following transportation options either alone or in combination for your current commute to your primary destination, **1 Cyclotron Rd, Berkeley, CA 94720, USA.**

	Today	In the past seven days	In the last month	In the last 12 months	At some point, but not in the last 12 months	Never	Not Applicable
Your own vehicle (single occupant)	○	○	○	○	○	○	○
Carpool with a friend, family member, colleague, or through Casual Carpool	○	○	○	○	○	○	○
Public mass transit - city bus	○	○	○	○	○	○	○
Public mass transit - other (e.g., BART, MUNI, train, ferry)	○	○	○	○	○	○	○
Private mass transit (e.g., company bus or shuttle)	○	○	○	○	○	○	○
Uber, Lyft, or similar app-based rideshare service **(single passenger option)**	○	○	○	○	○	○	○
Uber Pool, Lyft Line, or similar app-based rideshare service **(carpool option)**	○	○	○	○	○	○	○
Car-sharing services like Zipcar or Car2Go	○	○	○	○	○	○	○
Motorcycle, moped, or scooter	○	○	○	○	○	○	○
Bicycle or foot	○	○	○	○	○	○	○
Telecommute	○	○	○	○	○	○	○
Other [Please specify...]	○	○	○	○	○	○	○

« Previous | Next »

*QUESTION 1.4 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Please indicate whether you agree or disagree with the following statements.

	Agree	Disagree	Not Applicable
I have a driver's license	○	○	○
I prefer not to drive	○	○	○
I can't drive because of a disability, illness, or other limitation	○	○	○

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17%

*QUESTION 1.5 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Please indicate whether you would consider each of the items below to be a positive characteristic of a transportation option for you personally, or a negative characteristic.

	Positive	Negative
Ability to interact with people (other than close friends or family members)	○	○
Minimize environmental impacts	○	○

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20%

*QUESTION 1.6 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In this question think about how you decide which transportation option to use for your commute to your primary destination, **1 Cyclotron Rd, Berkeley, CA 94720, USA**. Please rate how important each of the following characteristics of transportation options are to you in this decision on a scale of 1= Not at all important, to 5= Very important. If the characteristic is something you have never actually thought about before in the context of transportation, please select that option as well.

	Not at all important (1)	Slightly important (2)	Moderately important (3)	Important (4)	Very important (5)	Not Applicable	I never thought about it before
Short travel time	○	○	○	○	○	○	☐
Shelter from bad weather	○	○	○	○	○	○	☐
Low cost	○	○	○	○	○	○	☐
Predictable arrival time	○	○	○	○	○	○	☐
Ability to engage in activities while traveling	○	○	○	○	○	○	☐
Ability to safely and conveniently transport a child under 8 years of age	○	○	○	○	○	○	☐
Ability to easily make more than one stop	○	○	○	○	○	○	☐
Low hassle	○	○	○	○	○	○	☐
Safety	○	○	○	○	○	○	☐
Maximize environmental impacts	○	○	○	○	○	○	☐
Predictable cost	○	○	○	○	○	○	☐
Not having to interact with people (other than close friends or family members)	○	○	○	○	○	○	☐

Row order randomized

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22%

QUESTION 1.6 (notes)

If respondent selected "Positive" for an option in QUESTION 1.5, that item is given a positive frame in QUESTION 1.6, and if they selected "Negative" for an option in QUESTION 1.5, that item is given a negative frame in QUESTION 1.6.

Positive Frame:

- *Ability to interact with people (other than close friends or family members)*
- *Minimize environmental impact*

Negative Frame:

- *Not having to interact with people (other than close friends or family members)*
- *Maximize environmental impact*

Content of the "info" icons:

- *Predictable arrival time: "knowing when you will arrive at your destination"*
- *Ability to engage in activities while traveling: "(e.g., work, reading, entertainment)"*
- *Low hassle: "(e.g., not having to transfer multiple times)"*
- *Predictable cost: "(e.g., cost doesn't vary like it does with Uber surge pricing)"*

QUESTION 1.7 (*Survey will not proceed unless they answer)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Please fill in how many times during a **RECENT TYPICAL WEEK** that you or someone in your household:

	Received a delivery from an online/phone order of...	**Took a vehicle** (e.g., personal vehicle, taxi, Uber, Lyft) to a store or restaurant to buy **primarily**...	**Walked, biked or used public transit** to get to a store or restaurant to buy **primarily**...	Did not purchase any of these items in a recent typical week
Groceries	0 deliveries	0 trips	0 trips	☐
Clothing, shoes or accessories	0 deliveries	0 trips	0 trips	☐
Household items	0 deliveries	0 trips	0 trips	☐
Prepared meal	0 deliveries	0 trips	0 trips	☐

Dropdown options: 0 deliveries, 1 delivery, 2 deliveries, …, 10 deliveries, more than 10 deliveries.

Dropdown options: 0 trips, 1 trip, 2 trips, …, 10 trips, more than 10 trips.

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25%

Content of "info" icons (same for both QUESTION 1.7 and QUESTION 1.8):

Groceries: "(e.g., cereal, meat, produce, dairy, beans)"

Household items: "(e.g., paper towels, diapers, cleaning products, sunscreen)"

Prepared meal: "(e.g., restaurant meals, take-out, meal delivery, cooking kit with prepared ingredients such as Blue Apron)"

QUESTION 1.8 *(*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*We want to understand how home delivery affects how many shopping trips you or others in your household have to take.

Imagine, hypothetically, **you could not order anything online and request home delivery**, so that you could not receive the deliveries you reported in the previous question.

Think about the **SAME RECENT TYPICAL WEEK**. Please indicate whether lack of home delivery during that week would require you or someone in your household to take **ADDITIONAL TRIPS** (beyond those you reported in the previous question) in order to make those purchases, or whether you would not make any additional trips (because you would be able to meet your needs by purchasing those items during trips you already reported in the previous question or by foregoing them altogether).

	Number of deliveries you reported in the previous question that you could no longer have delivered	If you could not have them delivered, the number of additional trips you would make to buy these items beyond the trips reported in the previous question		Would not have made any additional trips to buy these items if you couldn't have them delivered
		using a vehicle (e.g., personal vehicle, taxi, Uber, Lyft)	by walking, biking, or using public transit	
Groceries	1 delivery	0 additional trips	0 additional trips	☐
Clothing, shoes or accessories	1 delivery	0 additional trips	0 additional trips	☐
Household items	1 delivery	0 additional trips	0 additional trips	☐
Prepared meal	1 delivery	0 additional trips	0 additional trips	☐

Dropdown options: 0 additional trips, 1 additional trip, 2 additional trips, …, 10 additional trips, more than 10 additional trips.

Rows only appear in the table for QUESTION 1.8 if the respondent indicated they had one or more deliveries of that item when they answered QUESTION 1.7. If respondent indicated no deliveries in any of these four categories when answering QUESTION 1.7, then QUESTION 1.8 is skipped.

Your responses from the previous question for reference:

	Received a delivery from an online/phone order of...	Took a vehicle (e.g., personal vehicle, taxi, Uber, Lyft) to a store or restaurant to buy primarily...	Walked, biked, or used public transit to get to a store or restaurant to buy primarily...
Groceries	1	0	0
Clothing, shoes or accessories	1	0	0
Household items	1	0	0
Prepared meal	1	0	0

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27%

*QUESTION 1.9 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In general, what are the three things you like **MOST** about making purchases online with delivery rather than making purchases in a store?

Select up to three.

- [ ] More environmentally friendly
- [ ] Saves time
- [ ] More convenient
- [ ] More options
- [ ] Saves money
- [ ] Easier to compare options and prices
- [ ] Don't have to interact with another person
- [ ] Less hassle
- [ ] Other: Please specify...
- [ ] Not applicable

Order of rows randomized

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30%

*QUESTION 1.10 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In general, what are the three things you like **LEAST** about making purchases online with delivery rather than making purchases in a store?

Select up to three.

- ☐ Delivery charges
- ☐ Having to wait for delivery
- ☐ Less environmentally friendly
- ☐ Too much packaging to dispose of
- ☐ Harder to know exactly what you're getting (e.g., fit, fabric, quality, freshness)
- ☐ Less personal (i.e., don't get to interact with another person)
- ☐ Having to mail back returns
- ☐ Harder to browse and get ideas or get exposed to new items
- ☐ Not supporting local businesses
- ☐ Other: Please specify...
- ☐ Not applicable

Order of rows randomized

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32%

*QUESTION 1.11 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In the following table there are technologies listed down the rows on the left, and statements listed across the top. In each cell, please check the box if you would answer "YES" to that statement for that technology. If you would not answer "YES" to any of the statements for that technology, select Not Applicable. Select multiple statements for each technology, if applicable.

	I know of a close friend, coworker, or family member that owns this technology	I have used/ experienced this technology	I currently own or have owned this technology	I am interested in owning or using this technology in the future	I have never heard of this technology before now	Not Applicable
Hybrid vehicle (gasoline-electric)	☐	☐	☐	☐	☐	☐
Plug-in electric vehicles	☐	☐	☐	☐	☐	☐
Smart phone	☐	☐	☐	☐	☐	☐
Rooftop solar panels	☐	☐	☐	☐	☐	☐

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35%

*QUESTION 1.12 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In the following table there are automated or self-driving vehicle technologies listed down the rows on the left, and statements listed across the top. In each cell, please check the box if you would answer "YES" to that statement for that technology. If you would not answer "YES" to any of the statements for that technology, select Not Applicable. Select multiple statements for each technology, if applicable.

	I know of a close friend, coworker, or family member that has used/experienced this technology	I have used/experienced this technology	I currently own or have owned this technology	I am interested in owning or using this technology in the future	I have never heard of this technology before now	Not Applicable
Adaptive cruise control - brakes and accelerates to match the speed of the vehicle in front (only on highways), but requires driver to steer.	☐	☐	☐	☐	☐	☐
Partially automated - automatically brakes and accelerates, and additionally steers itself sufficiently to stay in a lane (only on highways), but requires the driver to be paying attention, to change lanes and be available to override (e.g., Tesla "Autopilot").	☐	☐	☐	☐	☐	☐
Fully automated - vehicle drives itself and does not require a driver to be paying attention (i.e., rider could sleep, read, work, or otherwise not pay attention to the road).	☐	☐	☐	☐	☐	☐

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37%

QUESTION 1.13 *(*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In the following table there are services listed down the rows on the left, and statements listed across the top. In each cell, please check the box if you would answer "YES" to that statement for that service. If you would not answer "YES" to any of the statements for that service, select Not Applicable. Select multiple statements for each service, if applicable.

	I know of a close friend, coworker, or family member that has used this service	I have used this service	I currently regularly use this service	I am interested in using this service in the future	I have never heard of this service before now	Not Applicable
Uber, Lyft, or similar app-based rideshare service **(single passenger option)**	☐	☐	☐	☐	☐	☐
Uber Pool, Lyft Line, or similar app-based rideshare service **(carpool option)**	☐	☐	☐	☐	☐	☐
Navigation or trip-planning apps (e.g., Google Maps, Apple Maps, WAZE)	☐	☐	☐	☐	☐	☐
Amazon Prime Account	☐	☐	☐	☐	☐	☐
Car-sharing services like Zipcar or Car2Go	☐	☐	☐	☐	☐	☐

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40%

QUESTION 1.14 *(*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*How many vehicle(s) (car, truck, SUV, van, or other passenger vehicle) are currently owned or leased by your household?

Please select...

Dropdown options:
0
1
2
3
4
5 or more

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42%

QUESTION 1.15 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Please fill out the following information for the vehicle (car, truck, SUV, van, or other passenger vehicle) that you drive most frequently. If you don't generally drive, then fill in the information of the vehicle that is driven the most frequently by anyone in your household.

Year [Please select...] *Dropdown options for "Year": 2018, 2017, …, 1981, 1980 or older*

Make [Please select...] *Dropdown options for "Make" and "Model" auto-populate from a databas makes and models. Once "Make" is filled in, "Model" narrows down to ju models of that make.*

Model [Please select...]

Fuel Type [Please select...] *Dropdown options for "Fuel Type": Gasoline; Diesel; Gasoline-Electric Hybrid; Plug-in Electric Hybrid; Plug-in all Electric; Ethanol; Hydrogen; Other*

What year was this vehicle purchased/acquired?

[Please select...] *Dropdown options: 2018, 2017, …, 1981, 1980 or earlier*

The number of days per week on average this vehicle is driven:

[Please select...] *Dropdown options: 0 days, 1 day, 2 days,…, 7 days.*

This vehicle is most often driven by:

[Please select...] *Dropdown options: me; someone else in my household*

« Previous | Next »

This question is skipped if respondent entered "0" in QUESTION 1.14.

*QUESTION 1.16 (*Survey will not proceed unless they answer)*

The prompt for this question is randomized across respondents. The following are the four treatments, corresponding to the two statements in green in the prompt:

*TREATMENT 1: with certainty it would cost you $0.2 per mile; a cost of $[0.2*distance]*
*TREATMENT 2: with certainty it would cost you $0.7 per mile; a cost of $[0.7*distance]*
*TREATMENT 3: with certainty it would cost you $1.2 per mile; a cost of $[1.2*distance]*
*TREATMENT 4: there would be a 50% chance that it would cost you $0.5 per mile, and a 50% chance that it would cost you $0.9 per mile; a 50% chance of it costing $[0.5*distance] and a 50% chance of it costing $[0.9*distance]*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

"distance"=miles between home address and primary destination location (calculated using goog router); location of home address is known, as the invitation letter is sent to an addres based sample, location of primary destination is from response to QUESTION 1.1.

*Imagine that you recently learned that **with certainty it would cost you $0.70 per mile** to take a ride-hailing service, such as Uber or Lyft. This would mean **a cost of $0.00** to take Uber or Lyft from your home to your primary destination, **1 Cyclotron Rd, Berkeley, CA 94720, USA**.

Given the above information about the cost of Uber or Lyft, please indicate for what amount of your commute to your primary destination you would choose to take each of the following modes on a typical day:

	The whole trip	Part of the trip
Your own vehicle	☐	☐
Public mass transit – other (e.g., BART, MUNI, train, ferry)	☐	☐
Walk (more than 5 minutes) or bike	☐	☐
Uber, Lyft, or similar app-based rideshare service	☐	☐
Public mass transit – city bus	☐	☐
Other	☐	☐

Order of rows is randomized.

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47%

Respondent cannot select "The whole trip" for more than one option, and cannot select "The whole trip" for one option and "Part of the trip" for another.

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Section 2. In this section we ask you some questions that let us understand more about your personality. The questions in this section may seem like they don't have much to do with your transportation decisions. However, research has shown that these types of questions do provide meaningful information that helps explain people's transportation choices.

Please click "Next" to continue.

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50%

*QUESTION 2.1 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Please rate your agreement with the following statements about your personality.

I see myself as someone who...	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
... is reserved	○	○	○	○	○
... is generally trusting	○	○	○	○	○
... tends to be lazy	○	○	○	○	○
... is relaxed, handles stress well	○	○	○	○	○
... has few artistic interests	○	○	○	○	○
... is outgoing, sociable	○	○	○	○	○
... tends to find fault with others	○	○	○	○	○
... does a thorough job	○	○	○	○	○
... gets nervous easily	○	○	○	○	○
... has an active imagination	○	○	○	○	○
... is considerate and kind to almost everyone	○	○	○	○	○

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52%

*QUESTION 2.2 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In each of the following hypothetical choices, please indicate whether you would prefer a **certain prize amount for sure (Option A)**, or whether you would rather **take the 50-50 chance at getting a higher prize amount (Option B)**. These choices are purely hypothetical.

	Option A	Option B (These are all the same)
Choice 1	$1 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 2	$10 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 3	$20 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 4	$30 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 5	$40 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 6	$50 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 7	$60 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 8	$70 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 9	$80 for sure	50% chance of winning $100, 50% chance of winning $0
Choice 10	$90 for sure	50% chance of winning $100, 50% chance of winning $0

"Rationality" is enforced; for example if respondent selects "$50 for sure" it is enforced that they also select the sure option of anything more than $50. And if they take the 50-50 chance instead of $60 for sure, it is enforced that they are also willing to take the 50-50 chance over anything less than $60 for sure.

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55%

QUESTION 2.3 *(*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In each of the following hypothetical choices, please indicate whether you would prefer **a prize amount today (Option A)**, or whether you would rather **wait for a higher prize amount in 3 months (Option B)**. These choices are purely hypothetical.

	Option A (These are all the same)	Option B
Choice 1	$100 today	$101 in 3 months
Choice 2	$100 today	$105 in 3 months
Choice 3	$100 today	$110 in 3 months
Choice 4	$100 today	$115 in 3 months
Choice 5	$100 today	$120 in 3 months
Choice 6	$100 today	$125 in 3 months
Choice 7	$100 today	$130 in 3 months
Choice 8	$100 today	$140 in 3 months
Choice 9	$100 today	$150 in 3 months
Choice 10	$100 today	$160 in 3 months

"Rationality" is enforced; for example if respondent selects "$115 in 3 months" it is enforced that they also select to wait 3 months for anything over $115. And if they take the $100 today instead of $125 in 3 months, it is enforced that they would also select $100 today over anything less than $125 in three months.

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57%

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Section 3: In this section we will ask you some basic demographic and household information.

Please click "Next" to continue.

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60%

*QUESTION 3.1 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*In what year were you born?

Year [Please select... ▾] *Dropdown options: 1999, 1998, 1997, …, 1900*

Note: they can only take the survey if they are 18 or over. The field year of the survey is 2017, so they can't have been born any more recent than 1999.

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62%

QUESTION 3.2 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Other [Please specify...]
- ◯ Prefer not to answer

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65%

QUESTION 3.3 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Which categories best describe you?

Select one or more boxes.

- ☐ White
- ☐ Hispanic, Latino, or Spanish origin
- ☐ Black or African American
- ☐ Asian
- ☐ Middle Eastern or North African
- ☐ American Indian or Alaska Native
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Some other race or origin [Please specify...]
- ☐ Prefer not to answer

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67%

QUESTION 3.4 (They can click “Next” and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

What is the highest level of education you’ve completed?

- ○ 12th grade or less, no diploma
- ○ High school diploma/GED
- ○ Some college
- ○ Associate’s degree
- ○ Bachelor’s degree
- ○ Master’s degree
- ○ Professional degree (for example: MD, DDS, DVM, JD)
- ○ Doctoral degree (for example: PhD, EdD)
- ○ None of the above
- ○ Prefer not to answer

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70%

QUESTION 3.5 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

What is your annual household income before taxes?

- ○ Less than $10,000
- ○ $10,000 to $14,999
- ○ $15,000 to $24,999
- ○ $25,000 to $34,999
- ○ $35,000 to $49,999
- ○ $50,000 to $74,999
- ○ $75,000 to $99,999
- ○ $100,000 to $149,999
- ○ $150,000 to $199,999
- ○ $200,000 to $299,999
- ○ $300,000 to $399,999
- ○ $400,000 or more
- ○ Prefer not to answer

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72%

QUESTION 3.6   (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Do you speak another language other than or in addition to English at home?

- ○ No
- ○ Yes [Please specify...]
- ○ Prefer not to answer

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75%

QUESTION 3.7 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Which of the following best describes your employment status?

Please select all that apply.

- [ ] Employed for wages
- [ ] Self-employed
- [ ] Out of work and looking for work
- [ ] Out of work but not currently looking for work
- [ ] A homemaker
- [ ] A student
- [ ] Military
- [ ] Retired
- [ ] Unable to work
- [ ] Prefer not to answer

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77%

QUESTION 3.8 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

Including yourself, how many people (including all adults and children) currently live in your household?

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7
- ○ 8
- ○ 9
- ○ 10 or more

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80%

QUESTION 3.9 (They can click "Next" and proceed without responding)

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

How many of the 5 people that live in your household are children under 8 years of age?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4

How many of the 5 people that live in your household currently have driver's licenses?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5

If they answered "1" to QUESTION 3.8, this question is skipped all together.

The set of options available in the first part of this question is their response to QUESTION 3.8 minus 1. So, for example, if they selected 5 in QUESTION 3.8, they can select between 0 and 4 of those household members being children. If they selected "10 or more" in QUESTION 3.8, the set of options in the first part of this question are: 0, 1, 2, 3, …, 8, 9 or more.

The set of options available in the second part of this question between 0 and their response to QUESTION 3.8. If they selected 5 in QUESTION 3.8, the response options for the second part of this question are 0, 1, 2, 3, 4, 5. If they selected "10 or more" in QUESTION 3.8, the set of options in the second part of this question are: 0, 1, 2, … 8, 9, 10 or more.

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82%

*QUESTION 3.10 (*Survey will not proceed unless they answer)*

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

*Which of the following transportation options did your **parent(s) or guardian(s)** use most frequently when you were in high school (14 – 18 years old)?

Select up to three.

- [ ] Public mass transit (e.g., train, tram, bus, ferry)
- [ ] Telecommute
- [ ] Private mass transit (e.g., company bus or shuttle)
- [ ] Drive own vehicle (single occupant)
- [ ] By bicycle or foot
- [ ] Carpool with at least one other person (including another adult household-member)
- [ ] Other

Order of rows is randomized.

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85%

WholeTraveler
TRANSPORTATION BEHAVIOR STUDY

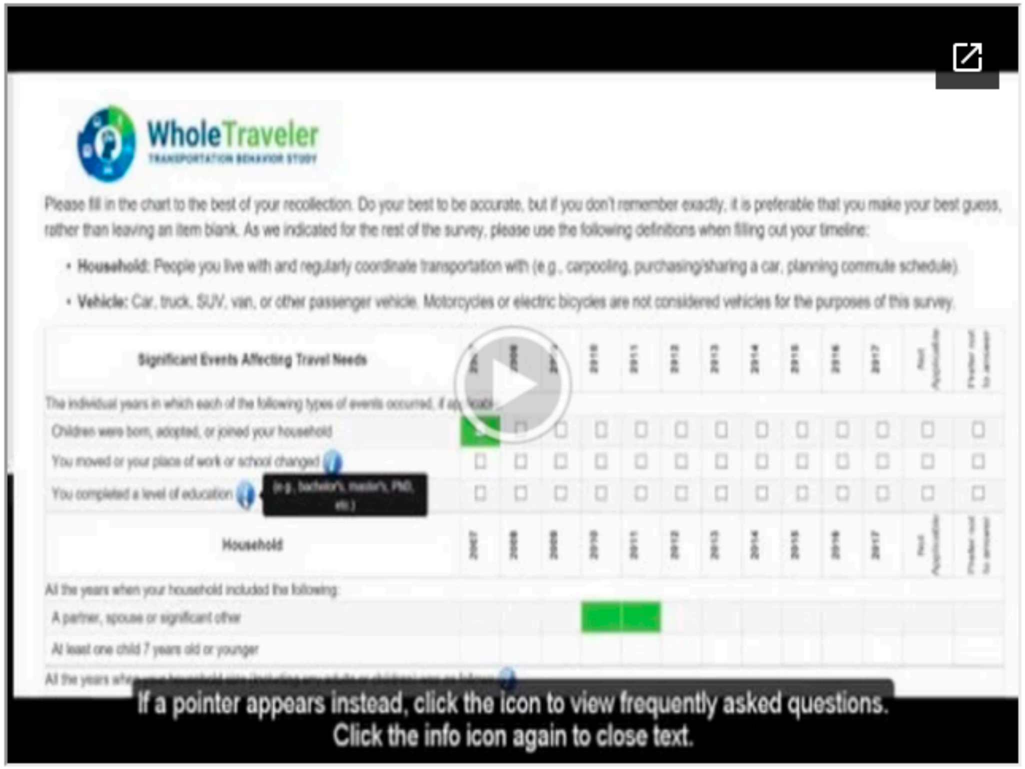
Section 4. In this last section of the survey we are going to ask you questions about life events and things that may have affected your transportation needs, options, and choices in your past. You will be shown a timeline of your life between the ages of 20 and up to age 50. You will be asked to indicate with a checkmark, or by selecting a time range, when various events occurred.

Click on the following video if you would like to see some more detailed instructions about how to fill in this portion of the survey.

Transcript of instruction video:

This video will show you how to fill out the life history section.

Each row represents an event or detail about your household. Each column represents one year. To make your selection, click directly on a box. The box will turn green once selected. To select multiple boxes at once, click one box, hold, drag your cursor, and release. To unselect a box, click the box again. To unselect multiple boxes at once, click one box, hold, drag, and release.



Transcript of instruction video (continued):

Info icons contain additional helpful information. Hover your cursor over any info icon to view text. If a pointer appears instead, click the icon to view frequently asked questions. Click the info icon again to close text.

Please fill in the chart to the best of your recollection. Do your best to be accurate, but if you don't remember exactly, it is preferable that you make your best guess, rather than leaving an item blank.

You may also select Not Applicable or Prefer not to answer.

If you have questions, email wholetraveler@rsginc.com.

Please click "Next" to continue.

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*QUESTION 4.1 (*Survey will not proceed unless they answer)*

Years shown are customized to respondent's birth year. It shows the years corresponding to when the correspondent was age 20 and up to the point when they were age 50. If they are under 20 years of age, this page (and the preceding instructional page) will be skipped.

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Please fill in the chart to the best of your recollection. Do your best to be accurate, but if you don't remember exactly, it is preferable that you make your best guess, rather than leaving an item blank. As we indicated for the rest of the survey, please use the following definitions when filling out your timeline:

- **Household:** People you live with and regularly coordinate transportation with (e.g., carpooling, purchasing/sharing a car, planning commute schedule).
- **Vehicle:** Car, truck, SUV, van, or other passenger vehicle. Motorcycles or electric bicycles are not considered vehicles for the purposes of this survey.

Significant Events Affecting Travel Needs	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Not Applicable	Prefer not to answer
The individual years in which each of the following types of events occurred, if applicable:																																	
Children were born, adopted, or joined your household	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
You moved or your place of work or school changed	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
You completed a level of education	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Household	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Not Applicable	Prefer not to answer
All the years when your household included the following:																																	
A partner, spouse or significant other																																	
At least one child 7 years old or younger																																	
All the years when your household size (including any adults or children) was as follows:																																	
1 member																																	
2 members																																	
3 members																																	
4 members																																	
5 or more members																																	
Employment and Education	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Not Applicable	Prefer not to answer
All the years when:																																	
You were working at least 35 hours per week on average																																	
You were enrolled in school or a training program																																	
Transportation Modes	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Not Applicable	Prefer not to answer
All the years when public mass transit was AVAILABLE to you to use, whether or not you did use it:																																	
Public mass transit was available																																	
All the years when you USED each of these modes for your commute to work, school, or other primary destination regularly (two or more times per week):																																	
Public mass transit																																	
Uber, Lyft, or similar app-based rideshare service																																	
Your own vehicle																																	
Walk or bike																																	

QUESTION 4.1 (continued) (*Survey will not proceed unless they answer)

Content of "info" icons:

- You moved or your place of work or school changed:
  "Frequently Asked Question: There were times when I moved multiple times in one year, how do I count that in the timeline?
  Answer: Regardless of how many times you moved in a year, simply indicate with a checkmark that you moved during that year."
- You completed a level of education: "(e.g., bachelor's, master's, PhD, etc.)"
- All the years when your household size…:
  "Frequently Asked Question: I lived with my roommate at one point, is my roommate part of my household?
  Answer: If you and your roommate regularly coordinated on transportation decisions, like deciding to purchase a car together, carpooling, etc., then yes. Otherwise, no.
  Frequently Asked Question: My living situation changed three times in one year with different combinations of people. Who do I say I lived with that year?
  Answer: Choose whatever answer you think best describes your living situation for the majority of that year."

Vehicle ownership	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Not Applicable	Prefer not to answer
All the years when your household had each of the indicated numbers of vehicles:																																	
No vehicle																																	
1 vehicle																																	
2 vehicles																																	
3 vehicles																																	
4 vehicles																																	
5 or more vehicles																																	

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90%

Content of "info" icons (continued):

- You were enrolled in school or a training program: "(e.g., college, trade school, internship, medical school, law school, city college, etc.)"
- All the years when public mass transit was AVAILABLE…:
  "Frequently Asked Question: It would have taken me two hours to get to work on the bus so it wasn't even close to an option for me, does that still mean it was available or not?
  Answer: Even if the mode option was really inconvenient, we still want to know that it technically existed, so please indicate that it was available."
- Public mass transit: "(e.g., bus, BART, MUNI, train, ferry)"
- All the years when your household had each of the indicated numbers of vehicles:
  "Frequently Asked Question: It's my wife's car, does that mean I should say I own it?
  Answer: We are interested in all vehicles in your household, so include your wife's car."

(They can click "Next" and proceed without responding)

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Please provide your email address so we can send you the $10 Amazon Gift Card for completing this survey:

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(They can click "Next" and proceed without responding - treated as a "No" response)

Thank you for completing the first phase of the WholeTraveler Transportation Behavior Study. You will be sent an email with your $10 Amazon Gift Card to the email address you provided as soon as possible.

You now have an opportunity to volunteer for Phase 2 of the study. Participation in Phase 2 is entirely voluntary.

A reminder of what's involved in Phase 2 of the study:

In the second phase you will follow some simple steps to provide a week's worth of your GPS Google Location History data. Google will collect these data using your smartphone through Google apps linked to your Google Account (such as Google Maps) while you go about your normal day-to-day activities for one week. The research team will not have direct access to your smartphone in any way. First, you will follow simple set-up steps. Then at the end of the week you will upload the data and answer a short set of questions about the transportation options you used during the week. All told, this will take 10-30 minutes.

In order to participate in Phase 2 of the study, you must meet the following requirements: (i) have personally participated in the Phase 1 online survey; (ii) be 18 years old or older; (iii) have access to a desktop or laptop computer; (iv) have an iOS or Android smartphone that you do not share with any other individual; and (v) either have or be willing to obtain a Google Account and have the Google Maps app installed on your smartphone (we will provide you with instructions for how to do both of these things). You will also need access to a desktop or laptop computer with Internet access to complete the final Google Location History data upload step.

If you submit one week's worth of GPS Google Location History data for this second phase of the study, you will receive a $20 payment. This is in addition to the $10 you will receive for having completed the Phase 1 survey. This payment will be in the form of an emailed Amazon Gift Card.

Risks and Confidentiality

By participating in Phase 2 there is a risk that your identity could be linked to the information you provide. In particular, through your GPS location data your common destinations, transportation patterns, or daily schedule could be observed. The primary risk to you would be unauthorized access to your data. There may also be other risks that we cannot predict.

Steps will be taken to ensure data security in order to minimize these risks. Data transfer and storage will follow industry best practices for security. In addition, access to the survey and GPS location-linked data will be highly controlled. An LBNL cyber security specialist has approved all data transfer, storage and access protocols.

If you participate in Phase 2 of this study and choose to provide us with your Google Location History data, be aware that Google collects those data and uses them for their own purposes. Google does not share those data with any companies, organizations or individuals outside of Google except under specific circumstances (with consent, with domain administrators, for external processing, or for legal reasons). While you need to allow Google to store your Location History over the course of a week if you want to participate in Phase 2 of this study, you can delete your Location History in-part or entirely, and turn off the preferences allowing Google to access or store those data, at any time. We will provide you with instructions for how to do this at the end of Phase 2. More information about Google's privacy policy can be found here:
https://static.googleusercontent.com/media/www.google.com/en//intl/en/policies/privacy/google_privacy_policy_en.pdf

Would you like to participate in Phase 2 of the WholeTraveler Transportation Behavior Study?

- ○ Yes
- ○ No

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(They can click “Next” and proceed without responding)

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Thank you for volunteering for Phase 2. We will email you some simple instructions for what to do next. Please confirm the email address where you would like us to send these instructions (Note: if you have a Gmail account, we suggest you provide that email address as it will simplify the set-up and data upload steps for Phase 2):

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Thank you for taking the time to complete this survey. All of your responses have been saved, so you may now exit your browser. For more information go to wholetraveler.lbl.gov.

Appendix D: Full OLS, Logistic Regression, and Alternate Approach Results

This appendix provides results tables for each of the technologies and services included in the paper body providing additional reporting of primary results, and including alternative OLS models and logistic regression specifications. The first set of tables present results from the primary regression reported in the table, but including all coefficients and reporting standard errors (the second OLS column under adoption and interest headings in Tables D1 – D8). The first OLS column reported in Tables D1 – D8 exclude $\mathbf{P'}_i$ variables described in Section 3 of the paper. The Logit column in Tables D1 – D8 report results from a logistic regression that parallels the specification for the linear probability models in the paper body.

In addition, Tables D9 – D11 report results are generated when the primary OLS regression specification is re-run but having omitted observations for which a respondent chose “not applicable” for at least one preference-over-mode-attribute variable. Finally, Table D12-D14 re-run this same primary OLS regression specification, but replacing instances in which a respondent chose “not applicable” in one of the preference-over-mode-attribute variables with the value 3.

Appendix Table D1: Adopted and Interested in Adopting for Ride-Hail Single Services

	Adopted			Interested in Adopting		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variables						
Born 1930s	0.0818	0.1238	0.7068	0.0916	0.1478	0.6600
	(0.57)	(0.87)	(0.78)	(0.66)	(1.05)	(0.84)
Born 1940s	-0.0821	-0.0730	-0.7740	0.0828	0.0920	0.5253
	(-1.46)	(-1.29)	(-1.41)	(1.04)	(1.12)	(1.28)
Born 1950s	-0.0055	-0.0055	-0.1307	0.0046	-0.0218	-0.0728
	(-0.11)	(-0.10)	(-0.36)	(0.07)	(-0.33)	(-0.20)
Born 1970s	0.0632	0.0622	0.3710	0.0028	-0.0048	-0.0175
	(1.24)	(1.21)	(1.19)	(0.05)	(-0.08)	(-0.05)
Born 1980s	0.2063***	0.2001***	1.0786***	0.1115*	0.1038*	0.5481*
	(4.21)	(3.98)	(3.70)	(1.82)	(1.65)	(1.74)

Born 1990s	0.2543***	0.2515***	1.3866***	0.1332*	0.1382*	0.7689*
	(4.18)	(4.00)	(4.05)	(1.71)	(1.69)	(1.88)
Any Children < 8yrs	-0.0654	-0.0526	-0.2503	-0.0629	-0.0649	-0.3333
	(-1.40)	(-1.11)	(-0.98)	(-1.12)	(-1.15)	(-1.11)
HH Income $75-150K	0.0345	0.0341	0.2074	0.0545	0.0311	0.1921
	(0.89)	(0.86)	(0.83)	(1.11)	(0.61)	(0.72)
HH Income $150-200K	0.0635	0.0654	0.3741	-0.0081	-0.0429	-0.1989
	(1.27)	(1.25)	(1.24)	(-0.13)	(-0.66)	(-0.56)
HH Income ≥ $200K	0.2032***	0.1833***	0.9916***	0.0751	0.0312	0.1870
	(4.23)	(3.62)	(3.59)	(1.21)	(0.50)	(0.58)
> 4yr College Ed.	0.0331	0.0392	0.2514	0.0190	0.0184	0.1072
	(1.01)	(1.18)	(1.33)	(0.47)	(0.46)	(0.53)
Female	0.0111	0.0090	0.0553	-0.0290	-0.0216	-0.1230
	(0.36)	(0.27)	(0.30)	(-0.76)	(-0.52)	(-0.58)
Location-based variables						
Contra Costa County	0.0123	0.0239	0.1566	-0.0211	-0.0210	-0.1167
	(0.23)	(0.45)	(0.48)	(-0.34)	(-0.33)	(-0.33)
Marin County	0.1213	0.1360	0.8071	0.1875	0.1943	0.9207*
	(1.28)	(1.42)	(1.54)	(1.48)	(1.60)	(1.72)
Napa County	0.0859	0.0928	0.5574	0.0097	0.0093	0.0316
	(0.62)	(0.66)	(0.75)	(0.05)	(0.05)	(0.03)
San Francisco County	0.1960***	0.2001***	0.9722***	0.0635	0.0517	0.2462
	(3.29)	(3.31)	(3.22)	(0.82)	(0.66)	(0.62)
San Mateo County	0.0290	0.0393	0.1560	0.1070	0.1202	0.5885
	(0.47)	(0.62)	(0.42)	(1.31)	(1.43)	(1.52)
Santa Clara County	0.0295	0.0440	0.2207	0.0388	0.0517	0.2626
	(0.65)	(0.97)	(0.88)	(0.68)	(0.91)	(0.94)
Solano County	-0.0576	-0.0406	-0.3373	-0.0052	0.0171	0.0846
	(-0.85)	(-0.60)	(-0.62)	(-0.06)	(0.19)	(0.17)
Sonoma County	-0.0098	-0.0022	-0.0866	-0.0933	-0.0942	-0.6508
	(-0.15)	(-0.03)	(-0.18)	(-1.25)	(-1.29)	(-1.29)
Res. Pop. Density	0.0003	0.0004	0.0015	-0.0020	-0.0019	-0.0101
	(0.16)	(0.26)	(0.19)	(-0.99)	(-0.96)	(-0.85)
P.D. Pop. Density	-0.0007	-0.0007	-0.0032	-0.0001	0.0000	0.0003
	(-0.55)	(-0.54)	(-0.48)	(-0.08)	(0.02)	(0.05)
Walk Score	0.0006	0.0005	0.0031	0.0006	0.0008	0.0047
	(0.83)	(0.62)	(0.69)	(0.64)	(0.85)	(0.93)
Dist. to P.D. (10,20]	-0.0170	-0.0032	0.0050	0.1351***	0.1506***	0.7665***
	(-0.45)	(-0.08)	(0.02)	(2.67)	(2.94)	(3.15)
Dist. to P.D. (20,50]	0.0306	0.0252	0.1344	0.0365	0.0503	0.2837
	(0.74)	(0.59)	(0.57)	(0.70)	(0.96)	(1.04)
Dist. to P.D. > 50mi	0.0654	0.0574	0.4260	0.0237	0.0363	0.2553
	(0.67)	(0.57)	(0.73)	(0.21)	(0.33)	(0.43)
Preference-over-mode-attribute variables						
Safety		0.0151	0.0900		-0.0033	-0.0142
		(0.99)	(0.97)		(-0.16)	(-0.14)
Low Cost		-0.0130	-0.0825		-0.0381*	-0.2095*
		(-0.81)	(-0.86)		(-1.86)	(-1.96)
Low Hassle		-0.0207	-0.1287		0.0205	0.1331
		(-1.11)	(-1.18)		(0.92)	(1.05)
Short Time		0.0102	0.0661		0.0445*	0.2486*
		(0.53)	(0.58)		(1.93)	(1.88)
Predict. Time		0.0097	0.0810		-0.0089	-0.0660
		(0.55)	(0.73)		(-0.36)	(-0.50)

Predict. Cost		0.0076	0.0298		-0.0007	0.0017
		(0.49)	(0.34)		(-0.03)	(0.02)
Multiple Stops		-0.0148	-0.0803		0.0006	0.0065
		(-1.31)	(-1.27)		(0.05)	(0.09)
Min. Env. Impact		0.0260***	0.1983***		-0.0018	-0.0042
		(3.35)	(3.00)		(-0.16)	(-0.07)
Social Interaction		-0.0058	-0.0341		-0.0086	-0.0470
		(-1.03)	(-1.06)		(-1.17)	(-1.23)
Personality and risk variables						
BFI Extraversion		0.0410**	0.2153**		0.0252	0.1256
		(2.47)	(2.28)		(1.21)	(1.18)
BFI Agreeableness		0.0210	0.1101		-0.0062	-0.0387
		(0.91)	(0.82)		(-0.22)	(-0.27)
BFI Conscientiousness		-0.0143	-0.0855		-0.0179	-0.0850
		(-0.69)	(-0.71)		(-0.69)	(-0.65)
BFI Neuroticism		-0.0020	-0.0223		-0.0138	-0.0656
		(-0.12)	(-0.23)		(-0.64)	(-0.60)
BFI Openness		0.0151	0.0974		0.0116	0.0600
		(0.85)	(0.98)		(0.47)	(0.48)
Risk Averse ($1-20)		-0.0124	-0.0558		-0.0752	-0.4003
		(-0.29)	(-0.23)		(-1.37)	(-1.36)
Risk Averse ($30-40)		-0.0420	-0.2620		-0.0078	-0.0027
		(-1.06)	(-1.18)		(-0.15)	(-0.01)
Risk Loving ($60+)		-0.0346	-0.1982		-0.0051	-0.0014
		(-0.73)	(-0.75)		(-0.09)	(-0.00)
Constant	0.0304	-0.2291	-4.1011***	0.1574*	0.1162	-2.0743*
	(0.42)	(-1.27)	(-3.74)	(1.75)	(0.53)	(-1.76)
Observations	826	826	826	587	587	587
Adjusted R^2	0.11	0.12		0.01	0.01	
Observations Y=1	239	239	239	170	170	170

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D2: Adopted and Interested in Adopting for Pooled Ride-Hail Services

	Adopted			**Interested in Adopting**		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variables						
Born 1930s	0.0476	0.1106	1.0679	-0.1872***	-0.1638**	
	(0.42)	(1.00)	(1.01)	(-3.72)	(-2.23)	
Born 1940s	-0.0461	-0.0580	-0.8209	-0.0859	-0.0925	-0.7040
	(-1.01)	(-1.22)	(-1.14)	(-1.43)	(-1.45)	(-1.34)
Born 1950s	-0.0407	-0.0455	-0.7408	-0.0485	-0.0552	-0.4149
	(-1.15)	(-1.25)	(-1.45)	(-0.97)	(-1.05)	(-1.12)
Born 1970s	0.0024	-0.0023	-0.1565	0.0212	0.0071	0.0200
	(0.06)	(-0.06)	(-0.37)	(0.42)	(0.14)	(0.06)

Born 1980s	0.1694***	0.1615***	1.1528***	0.0898*	0.0714	0.3715
	(3.99)	(3.76)	(3.22)	(1.70)	(1.33)	(1.24)
Born 1990s	0.2483***	0.2305***	1.4512***	0.1056	0.0997	0.5372
	(4.45)	(4.05)	(3.63)	(1.43)	(1.29)	(1.31)
Any Children < 8yrs	-0.0605	-0.0605	-0.4466	-0.0910*	-0.0875*	-0.5535*
	(-1.56)	(-1.52)	(-1.32)	(-1.95)	(-1.83)	(-1.79)
HH Income $75-150K	0.0491	0.0556	0.3969	0.0225	0.0085	0.0614
	(1.42)	(1.58)	(1.38)	(0.51)	(0.19)	(0.21)
HH Income $150-200K	0.0322	0.0562	0.3615	0.0304	0.0086	0.0557
	(0.77)	(1.29)	(1.04)	(0.56)	(0.15)	(0.16)
HH Income ≥ 200K	0.0269	0.0198	0.1248	0.0276	0.0011	0.0244
	(0.67)	(0.47)	(0.36)	(0.55)	(0.02)	(0.07)
> 4yr College Ed.	-0.0166	-0.0115	-0.1128	-0.0138	-0.0178	-0.1238
	(-0.62)	(-0.43)	(-0.50)	(-0.40)	(-0.51)	(-0.57)
Female	0.0069	-0.0010	-0.0457	-0.0306	-0.0403	-0.2542
	(0.26)	(-0.04)	(-0.20)	(-0.91)	(-1.10)	(-1.10)
<u>Location-based variables</u>						
Contra Costa County	-0.0529	-0.0433	-0.6117	-0.0055	-0.0047	-0.0286
	(-1.41)	(-1.13)	(-1.36)	(-0.10)	(-0.09)	(-0.09)
Marin County	0.1000	0.0847	0.6364	-0.0638	-0.0742	-0.4956
	(1.21)	(1.04)	(0.95)	(-0.72)	(-0.81)	(-0.70)
Napa County	-0.0929**	-0.0734*		-0.2349***	-0.2412***	
	(-2.31)	(-1.67)		(-4.99)	(-4.56)	
San Francisco County	0.0840	0.0838	0.4521	-0.0156	-0.0132	-0.1286
	(1.49)	(1.45)	(1.25)	(-0.23)	(-0.19)	(-0.32)
San Mateo County	-0.0105	0.0023	0.0367	-0.0438	-0.0367	-0.2361
	(-0.21)	(0.04)	(0.08)	(-0.71)	(-0.58)	(-0.58)
Santa Clara County	0.0078	0.0256	0.1542	-0.0209	-0.0047	-0.0414
	(0.20)	(0.67)	(0.52)	(-0.43)	(-0.10)	(-0.15)
Solano County	-0.0426	-0.0280	-0.3134	-0.0323	-0.0239	-0.1243
	(-0.78)	(-0.50)	(-0.47)	(-0.42)	(-0.30)	(-0.23)
Sonoma County	-0.0460	-0.0405	-0.7253	-0.0944	-0.0836	-0.7462
	(-0.98)	(-0.84)	(-0.98)	(-1.55)	(-1.37)	(-1.42)
Res. Pop. Density	0.0028	0.0024	0.0084	-0.0026	-0.0029*	-0.0175
	(1.58)	(1.33)	(0.74)	(-1.60)	(-1.70)	(-1.42)
P.D. Pop. Density	0.0003	0.0003	0.0020	-0.0001	0.0002	-0.0001
	(0.29)	(0.25)	(0.26)	(-0.05)	(0.16)	(-0.02)
Walk Score	0.0005	0.0007	0.0088	0.0016**	0.0016**	0.0107**
	(0.88)	(1.09)	(1.45)	(2.20)	(2.13)	(2.11)
Dist. to P.D. (10,20]	-0.0002	0.0050	0.0360	0.0048	0.0020	0.0347
	(-0.01)	(0.15)	(0.14)	(0.12)	(0.05)	(0.14)
Dist. to P.D. (20,50]	-0.0195	-0.0314	-0.2575	-0.0616	-0.0675	-0.4441
	(-0.58)	(-0.93)	(-0.81)	(-1.52)	(-1.64)	(-1.57)
Dist. to P.D. > 50mi	0.0208	0.0107	0.2824	0.0242	0.0277	0.2557
	(0.29)	(0.15)	(0.38)	(0.25)	(0.29)	(0.42)
<u>Preference-over-mode-attribute variables</u>						
Safety		-0.0088	-0.0749		-0.0077	-0.0435
		(-0.65)	(-0.62)		(-0.45)	(-0.41)
Low Cost		-0.0060	-0.0256		0.0038	0.0140
		(-0.44)	(-0.21)		(0.23)	(0.13)
Low Hassle		-0.0050	-0.0450		-0.0034	-0.0225
		(-0.33)	(-0.34)		(-0.18)	(-0.17)
Short Time		-0.0073	-0.0737		0.0103	0.0691
		(-0.47)	(-0.53)		(0.54)	(0.50)

Predict. Time		-0.0047	-0.0507		-0.0028	-0.0113
		(-0.31)	(-0.37)		(-0.13)	(-0.08)
Predict. Cost		0.0339***	0.2837**		-0.0029	-0.0225
		(2.65)	(2.43)		(-0.19)	(-0.23)
Multiple Stops		-0.0124	-0.0952		-0.0025	-0.0184
		(-1.32)	(-1.25)		(-0.22)	(-0.27)
Min. Env. Impact		0.0124*	0.1384*		0.0136*	0.1098*
		(1.93)	(1.65)		(1.80)	(1.72)
Social Interaction		-0.0003	0.0029		-0.0080	-0.0487
		(-0.07)	(0.07)		(-1.34)	(-1.30)
Personality and risk variables						
BFI Extraversion		0.0449***	0.3622***		0.0239	0.1488
		(3.23)	(3.08)		(1.40)	(1.44)
BFI Agreeableness		0.0464**	0.3933**		0.0176	0.1063
		(2.50)	(2.46)		(0.72)	(0.71)
BFI Conscientiousness		0.0004	0.0216		0.0090	0.0510
		(0.02)	(0.15)		(0.40)	(0.34)
BFI Neuroticism		0.0024	0.0472		0.0073	0.0481
		(0.16)	(0.39)		(0.39)	(0.43)
BFI Openness		-0.0028	-0.0402		-0.0185	-0.1286
		(-0.19)	(-0.34)		(-0.92)	(-1.03)
Risk Averse ($1-20)		-0.0052	-0.0589		-0.0480	-0.3354
		(-0.14)	(-0.20)		(-1.05)	(-1.11)
Risk Averse ($30-40)		-0.0317	-0.2465		0.0365	0.1984
		(-0.96)	(-0.92)		(0.84)	(0.81)
Risk Loving ($60+)		-0.0526	-0.4301		-0.0468	-0.3216
		(-1.36)	(-1.30)		(-0.99)	(-1.03)
Constant	0.0249	-0.2659*	-5.5402***	0.1928***	0.0772	-2.2143*
	(0.42)	(-1.76)	(-3.94)	(2.62)	(0.40)	(-1.71)
Observations	826	826	816	675	675	657
Adjusted R^2	0.13	0.15		0.02	0.01	
Observations Y=1	151	151	151	145	145	145

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D3: Adopted and Interested in Adopting for Car-Sharing

	Adopted			**Interested in Adopting**		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variables						
Born 1930s	0.0060	0.0230	--	-0.1328	-0.1290	-0.7808
	(0.47)	(0.95)		(-1.27)	(-1.04)	(-0.70)
Born 1940s	-0.0037	0.0020	--	-0.0451	-0.0563	-0.3635
	(-0.31)	(0.15)		(-0.69)	(-0.85)	(-0.85)
Born 1950s	0.0128	0.0122	0.6034	-0.0132	-0.0098	-0.0467
	(0.77)	(0.72)	(0.49)	(-0.24)	(-0.18)	(-0.14)

Born 1970s	-0.0031	-0.0009	0.1206	-0.1189**	-0.1234***	-0.8358***
	(-0.20)	(-0.05)	(0.11)	(-2.51)	(-2.62)	(-2.60)
Born 1980s	0.0152	0.0172	0.7704	-0.1005**	-0.1055**	-0.6124**
	(0.89)	(0.98)	(0.74)	(-2.18)	(-2.30)	(-2.25)
Born 1990s	0.0295	0.0390	1.7789	-0.0857	-0.0892	-0.5180
	(1.24)	(1.59)	(1.53)	(-1.46)	(-1.46)	(-1.40)
Any Children < 8yrs	0.0240	0.0235	1.1517	0.0234	0.0257	0.1807
	(1.16)	(1.09)	(1.46)	(0.56)	(0.59)	(0.57)
HH Income \$75-150K	0.0132	0.0161	1.0277	0.0726*	0.0787**	0.4941*
	(1.10)	(1.33)	(1.22)	(1.86)	(2.00)	(1.95)
HH Income \$150-200K	0.0091	0.0134	0.9737	0.0572	0.0729	0.4835
	(0.49)	(0.68)	(0.82)	(1.19)	(1.50)	(1.52)
HH Income ≥ \$200K	0.0325*	0.0352*	1.7439*	0.0179	0.0323	0.2031
	(1.75)	(1.87)	(1.96)	(0.43)	(0.76)	(0.68)
> 4yr College Ed.	0.0154	0.0163	0.8860	-0.0479	-0.0433	-0.2724
	(1.23)	(1.27)	(1.41)	(-1.58)	(-1.42)	(-1.34)
Female	-0.0127	-0.0125	-0.5254	-0.0760**	-0.0634**	-0.4239**
	(-1.10)	(-0.99)	(-1.02)	(-2.56)	(-2.01)	(-2.00)
Location-based variables						
Contra Costa County	0.0141	0.0148	1.3459	0.0037	0.0294	0.2121
	(0.78)	(0.76)	(1.17)	(0.07)	(0.59)	(0.66)
Marin County	-0.0010	0.0017	--	-0.1129	-0.0870	-0.7596
	(-0.09)	(0.12)		(-1.52)	(-1.23)	(-1.21)
Napa County	-0.0008	-0.0026	--	-0.1071	-0.0478	-0.5384
	(-0.05)	(-0.16)		(-1.02)	(-0.47)	(-0.50)
San Francisco County	0.0267	0.0312	0.7403	-0.0315	0.0063	0.0432
	(0.86)	(0.97)	(0.80)	(-0.52)	(0.10)	(0.12)
San Mateo County	0.0117	0.0094	0.2767	-0.1055**	-0.0855	-0.5855
	(0.49)	(0.38)	(0.29)	(-1.98)	(-1.52)	(-1.25)
Santa Clara County	-0.0070	-0.0068	-0.0913	-0.0752*	-0.0501	-0.3465
	(-0.52)	(-0.49)	(-0.11)	(-1.85)	(-1.21)	(-1.20)
Solano County	0.0002	-0.0023	--	0.0647	0.0740	0.4591
	(0.01)	(-0.18)		(0.76)	(0.87)	(0.93)
Sonoma County	0.0083	0.0033	--	-0.0457	-0.0395	-0.2361
	(0.76)	(0.25)		(-0.73)	(-0.64)	(-0.49)
Res. Pop. Density	0.0004	0.0003	-0.0005	0.0024	0.0021	0.0105
	(0.46)	(0.40)	(-0.04)	(1.41)	(1.21)	(1.13)
P.D. Pop. Density	-0.0003	-0.0004	-0.0153	0.0000	-0.0003	-0.0019
	(-0.87)	(-0.98)	(-0.75)	(0.00)	(-0.30)	(-0.29)
Walk Score	0.0006**	0.0006**	0.0499***	0.0011	0.0008	0.0057
	(2.38)	(2.50)	(3.40)	(1.59)	(1.14)	(1.16)
Dist. to P.D. (10,20]	-0.0080	-0.0046	-0.3090	-0.0036	0.0036	0.0475
	(-0.63)	(-0.36)	(-0.37)	(-0.10)	(0.10)	(0.21)
Dist. to P.D. (20,50]	0.0097	0.0112	0.3081	-0.0563	-0.0467	-0.3760
	(0.63)	(0.68)	(0.50)	(-1.57)	(-1.29)	(-1.37)
Dist. to P.D. > 50mi	-0.0173*	-0.0078	--	0.0048	0.0108	0.1366
	(-1.72)	(-0.63)		(0.05)	(0.11)	(0.22)
Preference-over-mode-attribute variables						
Safety		0.0049	0.3853*		0.0041	0.0076
		(1.19)	(1.77)		(0.30)	(0.08)
Low Cost		-0.0006	-0.1266		0.0041	0.0278
		(-0.09)	(-0.39)		(0.28)	(0.28)
Low Hassle		-0.0144*	-0.4673**		0.0013	-0.0023
		(-1.94)	(-2.41)		(0.07)	(-0.02)

Short Time		0.0050	0.0652		0.0179	0.1460
		(1.01)	(0.22)		(1.06)	(1.27)
Predict. Time		0.0077	0.3648		-0.0460**	-0.2701**
		(1.47)	(1.24)		(-2.22)	(-2.19)
Predict. Cost		-0.0000	-0.0275		0.0025	0.0089
		(-0.00)	(-0.10)		(0.18)	(0.09)
Multiple Stops		0.0035	0.1732		-0.0050	-0.0395
		(1.00)	(0.94)		(-0.46)	(-0.56)
Min. Env. Impact		0.0011	0.1683		0.0263***	0.2462***
		(0.38)	(0.92)		(3.88)	(3.31)
Social Interaction		0.0010	0.0796		0.0070	0.0501
		(0.39)	(0.65)		(1.30)	(1.31)
Personality and risk variables						
BFI Extraversion		0.0077	0.2129		-0.0117	-0.0948
		(1.06)	(0.67)		(-0.77)	(-0.90)
BFI Agreeableness		-0.0029	-0.1302		0.0356*	0.2294*
		(-0.42)	(-0.35)		(1.68)	(1.66)
BFI Conscientiousness		-0.0036	-0.3283		-0.0355*	-0.2423*
		(-0.53)	(-0.93)		(-1.74)	(-1.77)
BFI Neuroticism		-0.0061	-0.3287		0.0033	0.0265
		(-0.96)	(-1.19)		(0.20)	(0.23)
BFI Openness		0.0037	0.3178		0.0340**	0.2524**
		(0.52)	(0.84)		(2.01)	(2.06)
Risk Averse ($1-20)		0.0006	0.2017		-0.0013	0.0234
		(0.03)	(0.35)		(-0.03)	(0.08)
Risk Averse ($30-40)		-0.0106	-0.6361		0.0606	0.4152*
		(-0.70)	(-1.00)		(1.59)	(1.70)
Risk Loving ($60+)		-0.0302**	-2.1574**		-0.0283	-0.1652
		(-2.22)	(-2.12)		(-0.69)	(-0.57)
Constant	-0.0412**	-0.0638	-10.5306***	0.2484***	0.1332	-2.3974**
	(-2.17)	(-1.00)	(-3.15)	(3.40)	(0.77)	(-2.15)
Observations	826	826	645	804	804	804
Adjusted R^2	0.02	0.01		0.03	0.05	
Observations Y=1	22	22	22	167	167	167

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P}'_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X}'_{igc}$ and $\mathbf{P}'_i$.

Appendix Table D4: Adopted and Interested in Adopting for Hybrid Vehicles

	Adopted			Interested in Adopting		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variables						
Born 1930s	-0.0323	-0.0574	-0.5547	0.0713	0.1586	0.7398
	(-0.29)	(-0.48)	(-0.45)	(0.40)	(0.89)	(0.99)
Born 1940s	0.0732	0.0576	0.4749	-0.0701	-0.0557	-0.2524
	(1.08)	(0.86)	(1.12)	(-0.79)	(-0.64)	(-0.62)

Born 1950s	0.1631***	0.1626***	1.0500***	0.0216	0.0475	0.2140
	(3.13)	(3.06)	(3.43)	(0.29)	(0.65)	(0.67)
Born 1970s	-0.0615	-0.0645	-0.5636	0.0089	0.0105	0.0313
	(-1.45)	(-1.53)	(-1.62)	(0.14)	(0.17)	(0.11)
Born 1980s	-0.0958**	-0.0940**	-0.9108***	0.0420	0.0400	0.1849
	(-2.51)	(-2.43)	(-2.61)	(0.72)	(0.68)	(0.71)
Born 1990s	-0.0629	-0.0803*	-0.7583	0.1794**	0.1880***	0.8261***
	(-1.51)	(-1.79)	(-1.51)	(2.53)	(2.59)	(2.60)
Any Children < 8yrs	-0.0055	-0.0037	0.0078	-0.0421	-0.0103	-0.0528
	(-0.16)	(-0.10)	(0.02)	(-0.79)	(-0.19)	(-0.22)
HH Income $75-150K	0.0485	0.0545*	0.6523*	0.0484	0.0213	0.0865
	(1.56)	(1.72)	(1.95)	(0.96)	(0.43)	(0.40)
HH Income $150-200K	0.0764*	0.0841**	0.9073**	-0.0807	-0.1216*	-0.5556*
	(1.95)	(2.07)	(2.29)	(-1.28)	(-1.87)	(-1.90)
HH Income ≥ $200K	0.1258***	0.1316***	1.2323***	-0.1024*	-0.1583***	-0.7234***
	(3.41)	(3.36)	(3.41)	(-1.75)	(-2.62)	(-2.65)
> 4yr College Ed.	0.0849***	0.0933***	0.7763***	0.0403	0.0241	0.1151
	(3.24)	(3.54)	(3.39)	(1.01)	(0.60)	(0.65)
Female	0.0219	0.0382	0.3418	0.0348	0.0334	0.1586
	(0.85)	(1.35)	(1.41)	(0.89)	(0.80)	(0.87)
Location-based variables						
Contra Costa County	-0.0252	-0.0168	-0.1680	0.0158	0.0451	0.2025
	(-0.62)	(-0.40)	(-0.47)	(0.24)	(0.70)	(0.73)
Marin County	-0.1201*	-0.1059*	-1.0711	0.1689	0.1848	0.8152
	(-1.86)	(-1.78)	(-1.50)	(1.43)	(1.52)	(1.54)
Napa County	0.1719	0.2049	1.1656	-0.0597	-0.1539	-0.7045
	(1.17)	(1.41)	(1.57)	(-0.29)	(-0.85)	(-0.87)
San Francisco County	-0.0931**	-0.0873*	-0.7325	-0.1464**	-0.1137	-0.5404*
	(-2.09)	(-1.90)	(-1.56)	(-2.15)	(-1.62)	(-1.68)
San Mateo County	0.0406	0.0492	0.3572	0.0082	0.0346	0.1490
	(0.72)	(0.88)	(0.92)	(0.10)	(0.42)	(0.42)
Santa Clara County	-0.0317	-0.0320	-0.3279	-0.0233	0.0144	0.0584
	(-0.88)	(-0.86)	(-1.03)	(-0.42)	(0.26)	(0.24)
Solano County	0.0415	0.0550	0.4728	0.1390	0.1780*	0.7824*
	(0.61)	(0.80)	(0.94)	(1.37)	(1.75)	(1.79)
Sonoma County	0.0320	0.0351	0.2934	0.0468	0.0986	0.4410
	(0.51)	(0.54)	(0.62)	(0.47)	(0.97)	(0.99)
Res. Pop. Density	0.0009	0.0010	0.0095	-0.0005	-0.0004	-0.0017
	(1.04)	(1.11)	(1.15)	(-0.32)	(-0.27)	(-0.24)
P.D. Pop. Density	-0.0012	-0.0015*	-0.0161	-0.0024*	-0.0021	-0.0105
	(-1.52)	(-1.74)	(-1.44)	(-1.79)	(-1.54)	(-1.39)
Walk Score	0.0004	0.0003	0.0019	0.0015	0.0011	0.0050
	(0.66)	(0.55)	(0.40)	(1.64)	(1.19)	(1.24)
Dist. to P.D. (10,20]	0.0055	0.0081	0.0564	0.0059	0.0099	0.0596
	(0.18)	(0.26)	(0.20)	(0.12)	(0.20)	(0.28)
Dist. to P.D. (20,50]	0.0459	0.0455	0.3447	0.0209	0.0227	0.1019
	(1.25)	(1.23)	(1.25)	(0.39)	(0.43)	(0.44)
Dist. to P.D. > 50mi	-0.0320	-0.0529	-0.5007	-0.0052	-0.0172	-0.0606
	(-0.43)	(-0.67)	(-0.69)	(-0.05)	(-0.15)	(-0.12)
Preference-over-mode-attribute variables						
Safety		0.0023	0.0317		-0.0130	-0.0609
		(0.18)	(0.28)		(-0.67)	(-0.71)
Low Cost		0.0036	0.0102		0.0130	0.0532
		(0.27)	(0.09)		(0.66)	(0.60)

Low Hassle		0.0185	0.1444		0.0149	0.0705
		(1.22)	(1.02)		(0.69)	(0.70)
Short Time		-0.0209	-0.1623		0.0414*	0.1942*
		(-1.25)	(-1.28)		(1.84)	(1.86)
Predict. Time		-0.0258	-0.2133		0.0105	0.0489
		(-1.47)	(-1.62)		(0.42)	(0.44)
Predict. Cost		0.0066	0.0786		-0.0423**	-0.1882**
		(0.54)	(0.69)		(-2.27)	(-2.26)
Multiple Stops		-0.0071	-0.0721		-0.0198	-0.0881
		(-0.77)	(-0.90)		(-1.44)	(-1.47)
Min. Env. Impact		-0.0012	-0.0342		0.0192*	0.0942*
		(-0.14)	(-0.49)		(1.68)	(1.68)
Social Interaction		0.0003	0.0073		-0.0046	-0.0218
		(0.07)	(0.17)		(-0.66)	(-0.70)
Personality and risk variables						
BFI Extraversion		-0.0048	-0.0539		-0.0418**	-0.1929**
		(-0.38)	(-0.48)		(-2.00)	(-2.05)
BFI Agreeableness		0.0220	0.1850		0.0240	0.1156
		(1.17)	(1.11)		(0.80)	(0.87)
BFI Conscientiousness		-0.0325**	-0.2887**		0.0390	0.1779
		(-2.03)	(-2.25)		(1.52)	(1.54)
BFI Neuroticism		-0.0122	-0.1002		0.0004	-0.0012
		(-0.83)	(-0.75)		(0.02)	(-0.01)
BFI Openness		0.0102	0.0941		0.0253	0.1130
		(0.69)	(0.74)		(1.07)	(1.07)
Risk Averse ($1-20)		0.0026	0.0744		-0.0899*	-0.4070*
		(0.07)	(0.23)		(-1.67)	(-1.73)
Risk Averse ($30-40)		-0.0050	-0.0497		-0.0321	-0.1471
		(-0.16)	(-0.17)		(-0.66)	(-0.69)
Risk Loving ($60+)		0.0394	0.3391		-0.1400**	-0.6626**
		(1.02)	(1.04)		(-2.46)	(-2.50)
Constant	0.0560	0.1944	-1.5493	0.3486***	0.0748	-1.9723*
	(0.99)	(1.21)	(-1.21)	(3.82)	(0.31)	(-1.82)
Observations	826	826	826	699	699	699
Adjusted R^2	0.08	0.07		0.02	0.05	
Observations Y=1	127	127	127	306	306	306

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D5: Adopted and Interested in Adopting for Plug-in Electric Vehicles

	Adopted			**Interested in Adopting**		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variables						
Born 1930s	0.0229	0.0083	0.3900	-0.0505	0.0247	0.1074
	(0.20)	(0.08)	(0.34)	(-0.29)	(0.14)	(0.14)

Born 1940s	-0.0055	0.0078	0.3575	0.1246	0.1440*	0.6733*
	(-0.13)	(0.19)	(0.62)	(1.50)	(1.79)	(1.84)
Born 1950s	-0.0317	-0.0259	-0.3505	0.1023	0.1028	0.4730
	(-0.98)	(-0.79)	(-0.62)	(1.59)	(1.61)	(1.64)
Born 1970s	-0.0137	-0.0235	-0.5518	0.0898	0.0603	0.2760
	(-0.39)	(-0.67)	(-1.14)	(1.45)	(0.99)	(1.01)
Born 1980s	-0.0704***	-0.0835***	-1.6386***	0.1119**	0.0614	0.2884
	(-2.64)	(-3.12)	(-3.51)	(2.00)	(1.11)	(1.18)
Born 1990s	-0.0504*	-0.0644**	-1.3918	0.1223*	0.0792	0.3664
	(-1.76)	(-2.12)	(-1.61)	(1.75)	(1.13)	(1.18)
Any Children < 8yrs	0.0449	0.0569*	0.9018**	-0.0575	-0.0164	-0.0985
	(1.44)	(1.81)	(2.04)	(-1.06)	(-0.30)	(-0.40)
HH Income $75-150K	-0.0089	-0.0002	0.1731	0.0508	0.0332	0.1554
	(-0.51)	(-0.01)	(0.29)	(1.05)	(0.70)	(0.74)
HH Income $150-200K	0.0490*	0.0467*	0.8835	0.0995*	0.0820	0.3641
	(1.71)	(1.65)	(1.44)	(1.65)	(1.30)	(1.29)
HH Income ≥ $200K	0.0655**	0.0740**	1.5045***	0.1327**	0.0928	0.4243*
	(2.20)	(2.57)	(2.60)	(2.36)	(1.62)	(1.66)
> 4yr College Ed.	0.0314*	0.0298	0.5676*	0.1038***	0.0974**	0.4467***
	(1.74)	(1.65)	(1.65)	(2.71)	(2.57)	(2.63)
Female	-0.0268	-0.0102	-0.2736	-0.1104***	-0.0985**	-0.4481**
	(-1.41)	(-0.49)	(-0.68)	(-2.94)	(-2.44)	(-2.51)
Location-based variables						
Contra Costa County	0.0456	0.0495	0.6783	-0.0441	-0.0095	-0.0543
	(1.34)	(1.48)	(1.26)	(-0.68)	(-0.15)	(-0.19)
Marin County	0.0039	0.0249	0.5920	0.0356	0.0526	0.2583
	(0.06)	(0.41)	(0.66)	(0.34)	(0.49)	(0.53)
Napa County	-0.0800***	-0.0628**		-0.0137	0.0290	0.1395
	(-2.78)	(-2.26)		(-0.10)	(0.19)	(0.20)
San Francisco County	-0.0056	0.0125	0.3365	-0.1335**	-0.1126*	-0.5234*
	(-0.19)	(0.41)	(0.42)	(-1.98)	(-1.70)	(-1.76)
San Mateo County	-0.0043	-0.0138	-0.2082	-0.0798	-0.0483	-0.2300
	(-0.12)	(-0.40)	(-0.36)	(-1.08)	(-0.64)	(-0.70)
Santa Clara County	0.0173	0.0146	0.2700	-0.0611	-0.0192	-0.0912
	(0.65)	(0.55)	(0.52)	(-1.15)	(-0.36)	(-0.38)
Solano County	0.0252	0.0207	0.7485	-0.0278	0.0158	0.0922
	(0.50)	(0.41)	(0.94)	(-0.28)	(0.17)	(0.22)
Sonoma County	-0.0304	-0.0384	-1.2622	0.1457*	0.1796**	0.8351**
	(-1.04)	(-1.36)	(-1.29)	(1.72)	(2.18)	(2.14)
Res. Pop. Density	0.0002	-0.0000	-0.0091	-0.0003	-0.0002	-0.0005
	(0.40)	(-0.04)	(-0.47)	(-0.18)	(-0.10)	(-0.07)
P.D. Pop. Density	-0.0001	-0.0003	-0.0143	-0.0021	-0.0020	-0.0091
	(-0.28)	(-0.60)	(-0.98)	(-1.56)	(-1.57)	(-1.61)
Walk Score	-0.0003	-0.0005	-0.0033	0.0009	0.0004	0.0016
	(-0.71)	(-1.05)	(-0.42)	(1.09)	(0.44)	(0.40)
Dist. to P.D. (10,20]	0.0279	0.0325	0.4275	0.0642	0.0779*	0.3677*
	(1.23)	(1.40)	(0.98)	(1.46)	(1.80)	(1.86)
Dist. to P.D. (20,50]	0.0389	0.0426	0.6781*	-0.0163	-0.0218	-0.1016
	(1.44)	(1.64)	(1.70)	(-0.32)	(-0.44)	(-0.46)
Dist. to P.D. > 50mi	0.0121	0.0255	0.5989	-0.0117	-0.0178	-0.0433
	(0.22)	(0.46)	(0.76)	(-0.10)	(-0.15)	(-0.08)
Preference-over-mode-attribute variables						
Safety		-0.0040	-0.0831		-0.0162	-0.0735
		(-0.42)	(-0.53)		(-0.85)	(-0.85)

Low Cost		0.0261***	0.5110***		0.0063	0.0253
		(2.70)	(2.99)		(0.33)	(0.29)
Low Hassle		-0.0236**	-0.3478**		0.0137	0.0598
		(-2.02)	(-2.27)		(0.63)	(0.61)
Short Time		0.0047	0.0725		0.0412*	0.1962*
		(0.42)	(0.43)		(1.80)	(1.91)
Predict. Time		0.0130	0.3401		0.0068	0.0301
		(1.09)	(1.55)		(0.29)	(0.28)
Predict. Cost		-0.0208**	-0.4205**		-0.0281	-0.1332
		(-2.10)	(-2.48)		(-1.46)	(-1.49)
Multiple Stops		0.0032	0.0777		-0.0352***	-0.1607***
		(0.52)	(0.66)		(-2.63)	(-2.67)
Min. Env. Impact		0.0055	0.0899		0.0368***	0.1763***
		(0.80)	(0.50)		(3.11)	(2.95)
Social Interaction		0.0015	0.0198		-0.0098	-0.0471
		(0.42)	(0.28)		(-1.42)	(-1.50)
Personality and risk variables						
BFI Extraversion		-0.0116	-0.2410		0.0052	0.0240
		(-1.30)	(-1.33)		(0.27)	(0.28)
BFI Agreeableness		0.0096	0.1745		0.0652**	0.3014**
		(0.76)	(0.75)		(2.38)	(2.39)
BFI Conscientiousness		-0.0408***	-0.8503***		-0.0453*	-0.2121*
		(-3.35)	(-3.98)		(-1.90)	(-1.93)
BFI Neuroticism		-0.0038	-0.0520		0.0019	0.0121
		(-0.46)	(-0.30)		(0.09)	(0.13)
BFI Openness		0.0059	0.1381		0.0259	0.1237
		(0.63)	(0.78)		(1.24)	(1.30)
Risk Averse ($1-20)		-0.0421*	-1.0137**		-0.0772	-0.3578
		(-1.74)	(-1.96)		(-1.50)	(-1.58)
Risk Averse ($30-40)		-0.0329	-0.5496		0.0200	0.0833
		(-1.34)	(-1.44)		(0.42)	(0.39)
Risk Loving ($60+)		-0.0467*	-0.8570*		-0.1561***	-0.7058***
		(-1.74)	(-1.66)		(-2.87)	(-2.94)
Constant	0.0649	0.2318**	-0.8619	0.4183***	0.1758	-1.5226
	(1.49)	(2.06)	(-0.43)	(4.82)	(0.80)	(-1.50)
Observations	826	826	816	772	772	772
Adjusted R^2	0.04	0.06		0.03	0.07	
Observations Y=1	54	54	54	426	426	426

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D6: Adopted and Interested in Adopting for Adaptive Cruise Control

	Adopted			Interested in Adopting		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variable						

Born 1930s	-0.0776	-0.0414	-0.6891	0.0428	0.0233	0.0997
	(-0.71)	(-0.36)	(-0.59)	(0.22)	(0.11)	(0.11)
Born 1940s	0.0383	0.0271	0.2307	0.0621	0.0698	0.3201
	(0.57)	(0.42)	(0.55)	(0.69)	(0.74)	(0.78)
Born 1950s	-0.0788*	-0.0960**	-0.8104**	0.0601	0.0647	0.2927
	(-1.72)	(-2.07)	(-2.03)	(0.89)	(0.92)	(0.98)
Born 1970s	-0.0298	-0.0305	-0.1767	0.0116	0.0167	0.0666
	(-0.64)	(-0.66)	(-0.54)	(0.18)	(0.25)	(0.23)
Born 1980s	-0.0248	-0.0160	-0.1028	0.0177	0.0046	0.0197
	(-0.57)	(-0.36)	(-0.32)	(0.29)	(0.07)	(0.08)
Born 1990s	-0.0582	-0.0706	-0.5903	0.0970	0.1043	0.4667
	(-1.25)	(-1.45)	(-1.32)	(1.30)	(1.37)	(1.42)
Any Child < 8yrs	0.0587	0.0356	0.2081	-0.0993*	-0.0739	-0.3353
	(1.36)	(0.82)	(0.76)	(-1.77)	(-1.29)	(-1.34)
HH Income $75-150K	0.0435	0.0427	0.4527	0.0643	0.0487	0.2177
	(1.35)	(1.32)	(1.53)	(1.26)	(0.93)	(0.97)
HH Income $150-200K	0.0540	0.0513	0.4876	0.1475**	0.1128*	0.4964*
	(1.25)	(1.18)	(1.33)	(2.26)	(1.67)	(1.73)
HH Income ≥ $200K	0.1112***	0.1131***	0.9417***	0.1694***	0.1115*	0.4892*
	(2.76)	(2.83)	(2.91)	(2.90)	(1.83)	(1.88)
> 4yr College Ed.	0.0173	0.0255	0.1799	0.0520	0.0458	0.2092
	(0.62)	(0.92)	(0.85)	(1.26)	(1.09)	(1.18)
Female	0.0022	-0.0070	-0.0846	-0.1524***	-0.1576***	-0.6842***
	(0.08)	(-0.25)	(-0.39)	(-3.86)	(-3.74)	(-3.84)
Location-based variable						
Contra Costa County	0.0875*	0.0907*	0.6445*	0.0066	0.0030	0.0114
	(1.76)	(1.80)	(1.81)	(0.10)	(0.04)	(0.04)
Marin County	0.0130	-0.0066	0.0273	0.1509	0.1552	0.7340
	(0.17)	(-0.09)	(0.05)	(1.48)	(1.50)	(1.48)
Napa County	0.0705	0.0762	0.5619	-0.1242	-0.1696	-0.7441
	(0.53)	(0.57)	(0.53)	(-0.76)	(-0.99)	(-0.97)
San Francisco County	-0.0383	-0.0500	-0.4042	0.0096	-0.0075	-0.0329
	(-0.85)	(-1.10)	(-0.96)	(0.14)	(-0.10)	(-0.11)
San Mateo County	0.0093	0.0204	0.1989	-0.0255	-0.0314	-0.1406
	(0.18)	(0.40)	(0.50)	(-0.32)	(-0.39)	(-0.41)
Santa Clara County	0.0220	0.0169	0.1407	-0.0037	0.0057	0.0341
	(0.56)	(0.43)	(0.47)	(-0.07)	(0.10)	(0.14)
Solano County	0.1410*	0.1479*	1.0916**	-0.0328	0.0048	0.0276
	(1.78)	(1.89)	(2.25)	(-0.31)	(0.04)	(0.06)
Sonoma County	0.0438	0.0374	0.3359	0.0333	0.0536	0.2417
	(0.71)	(0.59)	(0.68)	(0.35)	(0.56)	(0.59)
Res. Pop. Density	-0.0007	-0.0008	-0.0096	-0.0008	-0.0002	-0.0010
	(-0.64)	(-0.68)	(-0.71)	(-0.44)	(-0.13)	(-0.13)
P.D. Pop. Density	-0.0009	-0.0011	-0.0092	0.0008	0.0015	0.0066
	(-1.07)	(-1.26)	(-1.14)	(0.48)	(0.94)	(1.00)
Walk Score	0.0004	0.0008	0.0069	-0.0003	-0.0006	-0.0027
	(0.55)	(1.17)	(1.34)	(-0.29)	(-0.64)	(-0.67)
Dist. to P.D. (10,20]	-0.0045	-0.0028	-0.0491	0.0453	0.0509	0.2375
	(-0.13)	(-0.08)	(-0.19)	(0.93)	(1.02)	(1.11)
Dist. to P.D. (20,50]	-0.0050	-0.0028	-0.0647	0.0337	0.0355	0.1614
	(-0.13)	(-0.07)	(-0.23)	(0.63)	(0.66)	(0.70)
Dist. to P.D. > 50mi	0.0053	-0.0240	-0.2529	0.0283	-0.0056	-0.0157
	(0.06)	(-0.29)	(-0.47)	(0.24)	(-0.05)	(-0.03)
Preference-over-mode-attribute variables						

Safety		-0.0054	-0.0501		-0.0059	-0.0297
		(-0.40)	(-0.48)		(-0.29)	(-0.34)
Low Cost		-0.0033	-0.0300		-0.0135	-0.0593
		(-0.24)	(-0.27)		(-0.64)	(-0.65)
Low Hassle		0.0151	0.0882		-0.0157	-0.0670
		(0.98)	(0.67)		(-0.68)	(-0.69)
Short Time		0.0227	0.2401*		0.0188	0.0821
		(1.59)	(1.81)		(0.80)	(0.80)
Predict. Time		-0.0146	-0.1438		0.0040	0.0164
		(-0.88)	(-1.04)		(0.16)	(0.15)
Predict. Cost		0.0169	0.1512		-0.0212	-0.0934
		(1.25)	(1.38)		(-1.07)	(-1.10)
Multiple Stops		0.0130	0.1022		-0.0154	-0.0698
		(1.28)	(1.31)		(-1.05)	(-1.11)
Min. Env. Impact		-0.0242***	-0.1716***		0.0188	0.0875
		(-2.67)	(-3.00)		(1.44)	(1.45)
Social Interaction		0.0019	0.0173		-0.0168**	-0.0759**
		(0.38)	(0.46)		(-2.23)	(-2.30)
Personality and risk variables						
BFI Extraversion		-0.0053	-0.0414		0.0151	0.0684
		(-0.37)	(-0.37)		(0.73)	(0.76)
BFI Agreeableness		0.0448**	0.3885**		-0.0017	-0.0101
		(2.20)	(2.29)		(-0.06)	(-0.08)
BFI Conscientiousness		0.0149	0.1078		0.0251	0.1151
		(0.92)	(0.85)		(0.99)	(1.05)
BFI Neuroticism		0.0011	0.0364		0.0080	0.0339
		(0.08)	(0.32)		(0.36)	(0.36)
BFI Openness		0.0024	-0.0062		-0.0040	-0.0146
		(0.15)	(-0.05)		(-0.17)	(-0.15)
Risk Averse ($1-20)		-0.0471	-0.4827		-0.0628	-0.2772
		(-1.35)	(-1.50)		(-1.17)	(-1.22)
Risk Averse ($30-40)		-0.0093	-0.0749		-0.1060**	-0.4648**
		(-0.27)	(-0.28)		(-2.09)	(-2.13)
Risk Loving ($60+)		0.1254***	0.8054***		-0.1198*	-0.5280**
		(2.74)	(2.79)		(-1.96)	(-2.01)
Constant	0.1054	-0.2210	-5.0199***	0.4265***	0.4870**	-0.0898
	(1.61)	(-1.43)	(-3.84)	(4.54)	(2.06)	(-0.09)
Observations	826	826	826	688	688	688
Adjusted R^2	0.01	0.04		0.03	0.03	
Observations Y=1	138	138	138	329	329	329

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D7: Adopted and Interested in Adopting for Partially Automated Vehicle Technology

	Adopted			Interested in Adopting		
	OLS	OLS	Logit	OLS	OLS	Logit
Demographic variables						
Born 1930s	0.0656	0.0651	1.0430	0.0968	0.1270	0.5780
	(0.65)	(0.66)	(0.95)	(0.50)	(0.63)	(0.62)
Born 1940s	0.0336	0.0269	0.6319	0.2132***	0.2159***	0.9733***
	(0.85)	(0.69)	(0.85)	(2.66)	(2.61)	(2.59)
Born 1950s	-0.0243	-0.0300	-1.1574	0.0733	0.0615	0.2792
	(-1.09)	(-1.31)	(-1.30)	(1.19)	(0.97)	(1.00)
Born 1970s	0.0168	0.0169	0.3374	0.0660	0.0511	0.2219
	(0.62)	(0.62)	(0.51)	(1.13)	(0.86)	(0.85)
Born 1980s	0.0017	0.0059	0.0962	0.0837	0.0637	0.2804
	(0.09)	(0.28)	(0.18)	(1.58)	(1.17)	(1.17)
Born 1990s	-0.0086	-0.0115	-0.5928	0.2515***	0.2218***	0.9816***
	(-0.43)	(-0.52)	(-0.68)	(3.68)	(3.16)	(3.17)
Any Children < 8yrs	-0.0135	-0.0180	-0.6360	-0.0474	-0.0425	-0.1859
	(-0.64)	(-0.83)	(-1.00)	(-0.92)	(-0.80)	(-0.81)
HH Income $75-150K	0.0050	0.0089	0.2597	0.0795*	0.0686	0.3134
	(0.30)	(0.52)	(0.43)	(1.68)	(1.41)	(1.47)
HH Income $150-200K	0.0013	0.0024	-0.0318	0.0859	0.0567	0.2604
	(0.07)	(0.12)	(-0.05)	(1.44)	(0.93)	(0.98)
HH Income ≥ $200K	0.0390*	0.0434**	0.9756*	0.1963***	0.1502***	0.6695***
	(1.82)	(2.03)	(1.86)	(3.64)	(2.66)	(2.69)
> 4yr College Ed.	0.0036	0.0034	0.0886	0.0312	0.0260	0.1181
	(0.25)	(0.24)	(0.21)	(0.82)	(0.68)	(0.71)
Female	-0.0233*	-0.0273*	-0.9513**	-0.1755***	-0.1579***	-0.6874***
	(-1.74)	(-1.84)	(-1.99)	(-4.84)	(-4.04)	(-4.12)
Location-based variables						
Contra Costa County	0.0388	0.0364	0.9218	0.0450	0.0413	0.1789
	(1.53)	(1.42)	(1.47)	(0.71)	(0.65)	(0.64)
Marin County	0.0401	0.0236	0.3032	0.1998**	0.1908**	0.8956*
	(0.75)	(0.46)	(0.33)	(2.16)	(2.01)	(1.91)
Napa County	0.0724	0.0625	1.3404	-0.1422	-0.1340	-0.5916
	(0.74)	(0.62)	(0.85)	(-0.91)	(-0.87)	(-0.82)
San Francisco County	-0.0201	-0.0238	-0.9304	-0.0059	-0.0249	-0.1118
	(-0.87)	(-0.99)	(-0.97)	(-0.09)	(-0.38)	(-0.39)
San Mateo County	0.0127	0.0103	0.2239	0.0000	-0.0106	-0.0501
	(0.43)	(0.35)	(0.27)	(0.00)	(-0.15)	(-0.16)
Santa Clara County	0.0009	-0.0015	-0.0014	-0.0215	-0.0130	-0.0545
	(0.05)	(-0.08)	(-0.00)	(-0.42)	(-0.25)	(-0.24)
Solano County	0.0688	0.0723	2.0291**	-0.0147	0.0043	0.0301
	(1.42)	(1.47)	(2.31)	(-0.16)	(0.04)	(0.07)
Sonoma County	0.0019	0.0001	-0.2609	-0.0059	-0.0029	-0.0253
	(0.08)	(0.01)	(-0.25)	(-0.07)	(-0.03)	(-0.07)
Res. Pop. Density	0.0007	0.0005	0.0174	0.0001	0.0004	0.0017
	(0.87)	(0.73)	(1.25)	(0.07)	(0.24)	(0.25)
P.D. Pop. Density	0.0000	0.0000	0.0017	-0.0003	-0.0001	-0.0004
	(0.03)	(0.04)	(0.11)	(-0.21)	(-0.06)	(-0.06)

Walk Score	-0.0002	-0.0001	0.0016	-0.0006	-0.0008	-0.0037
	(-0.58)	(-0.23)	(0.17)	(-0.74)	(-0.98)	(-1.00)
Dist. to P.D. (10,20]	0.0294	0.0291	0.8629*	0.0244	0.0322	0.1494
	(1.42)	(1.40)	(1.93)	(0.54)	(0.70)	(0.73)
Dist. to P.D. (20,50]	-0.0074	-0.0038	0.0499	0.0156	0.0128	0.0582
	(-0.41)	(-0.21)	(0.09)	(0.33)	(0.27)	(0.28)
Dist. to P.D. > 50mi	-0.0183	-0.0264	-0.4155	-0.0147	-0.0231	-0.1110
	(-0.48)	(-0.68)	(-0.41)	(-0.13)	(-0.21)	(-0.23)
Preference-over-mode-attribute variables						
Safety		-0.0126	-0.3069**		-0.0244	-0.1110
		(-1.44)	(-1.97)		(-1.32)	(-1.35)
Low Cost		0.0114	0.3710		-0.0164	-0.0726
		(1.21)	(1.54)		(-0.86)	(-0.86)
Low Hassle		0.0082	0.2188		0.0068	0.0340
		(0.94)	(0.94)		(0.32)	(0.35)
Short Time		-0.0023	-0.0169		0.0276	0.1256
		(-0.31)	(-0.08)		(1.25)	(1.27)
Predict. Time		-0.0021	-0.1373		0.0027	0.0137
		(-0.21)	(-0.50)		(0.12)	(0.13)
Predict. Cost		-0.0014	-0.0832		-0.0022	-0.0107
		(-0.17)	(-0.45)		(-0.12)	(-0.13)
Multiple Stops		0.0086	0.2625		-0.0077	-0.0352
		(1.50)	(1.63)		(-0.57)	(-0.60)
Min. Env. Impact		-0.0122**	-0.3169***		0.0203*	0.0952*
		(-2.07)	(-3.54)		(1.94)	(1.90)
Social Interaction		0.0012	0.0353		-0.0038	-0.0189
		(0.38)	(0.46)		(-0.57)	(-0.63)
Personality and risk variables						
BFI Extraversion		-0.0020	-0.0351		0.0183	0.0839
		(-0.31)	(-0.21)		(0.95)	(1.00)
BFI Agreeableness		0.0048	0.1524		0.0057	0.0303
		(0.41)	(0.47)		(0.21)	(0.26)
BFI Conscientiousness		0.0111	0.2291		-0.0151	-0.0649
		(1.22)	(0.88)		(-0.64)	(-0.62)
BFI Neuroticism		0.0011	0.0686		-0.0002	0.0000
		(0.16)	(0.31)		(-0.01)	(0.00)
BFI Openness		0.0026	-0.0221		-0.0090	-0.0407
		(0.28)	(-0.09)		(-0.41)	(-0.42)
Risk Averse ($1-20)		-0.0232	-0.7746		-0.1470***	-0.6563***
		(-1.20)	(-1.28)		(-2.87)	(-2.95)
Risk Averse ($30-40)		-0.0295	-0.8502		-0.1003**	-0.4456**
		(-1.60)	(-1.45)		(-2.17)	(-2.24)
Risk Loving ($60+)		0.0065	0.0598		-0.1002*	-0.4425*
		(0.26)	(0.11)		(-1.81)	(-1.87)
Constant	0.0272	-0.0176	-5.1774*	0.4083***	0.5026**	-0.0674
	(0.94)	(-0.19)	(-1.94)	(5.08)	(2.33)	(-0.07)
Observations	826	826	826	793	793	793
Adjusted R^2	0.00	0.01		0.05	0.06	
Observations Y=1	33	33	33	384	384	384

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics reported in parentheses. ‘OLS’ models report results generated using a linear probability model, while ‘logit’ results were produced using logistic regression. The dependent variable = 1 in ‘Adopted’ models when the respondent has adopted the technology. ‘Interested in Adopting’ uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each

section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D8: Interested in Adopting for Fully Automated Technology

	Interested in Adopting		
	OLS	OLS	Logit
Demographic variables			
Born 1930s	0.0591	0.1024	0.4805
	(0.33)	(0.55)	(0.53)
Born 1940s	0.0520	0.0491	0.2194
	(0.67)	(0.62)	(0.61)
Born 1950s	0.0137	0.0076	0.0335
	(0.23)	(0.12)	(0.12)
Born 1970s	-0.0461	-0.0554	-0.2659
	(-0.83)	(-0.98)	(-1.02)
Born 1980s	0.0581	0.0497	0.2285
	(1.15)	(0.97)	(0.97)
Born 1990s	0.2359***	0.2297***	1.0942***
	(3.73)	(3.48)	(3.41)
Any Children < 8yrs	0.0353	0.0351	0.1574
	(0.72)	(0.69)	(0.69)
HH Income \$75-150K	0.1169**	0.1083**	0.5047**
	(2.56)	(2.34)	(2.37)
HH Income \$150-200K	0.1416**	0.1186**	0.5536**
	(2.53)	(2.05)	(2.11)
HH Income ≥ \$200K	0.2216***	0.1934***	0.9089***
	(4.38)	(3.64)	(3.67)
> 4yr College Ed.	0.0379	0.0341	0.1549
	(1.06)	(0.95)	(0.94)
Female	-0.2635***	-0.2600***	-1.1577***
	(-7.60)	(-6.91)	(-6.81)
Location-based variables			
Contra Costa County	-0.0187	-0.0244	-0.1088
	(-0.31)	(-0.40)	(-0.39)
Marin County	0.0048	0.0068	0.0475
	(0.05)	(0.07)	(0.10)
Napa County	0.0247	0.0108	0.0762
	(0.17)	(0.07)	(0.12)
San Francisco County	0.0858	0.0833	0.3968
	(1.39)	(1.34)	(1.36)
San Mateo County	0.0038	-0.0070	-0.0166
	(0.06)	(-0.11)	(-0.05)
Santa Clara County	0.0279	0.0334	0.1647
	(0.57)	(0.67)	(0.72)
Solano County	0.0559	0.0716	0.3384
	(0.60)	(0.74)	(0.78)
Sonoma County	0.0827	0.0882	0.4123
	(0.97)	(1.01)	(1.00)

Res. Pop. Density	-0.0021	-0.0020	-0.0095
	(-1.49)	(-1.39)	(-1.36)
P.D. Pop. Density	0.0018	0.0018	0.0092
	(1.33)	(1.40)	(1.43)
Walk Score	0.0004	0.0003	0.0016
	(0.50)	(0.39)	(0.43)
Dist. to P.D. (10,20]	0.0079	0.0085	0.0512
	(0.18)	(0.20)	(0.26)
Dist. to P.D. (20,50]	-0.0196	-0.0177	-0.0706
	(-0.44)	(-0.39)	(-0.34)
Dist. to P.D. > 50mi	-0.0441	-0.0430	-0.2087
	(-0.40)	(-0.38)	(-0.40)
Preference-over-mode-attribute variables			
Safety		0.0036	0.0122
		(0.21)	(0.15)
Low Cost		-0.0063	-0.0296
		(-0.35)	(-0.35)
Low Hassle		0.0173	0.0803
		(0.87)	(0.87)
Short Time		-0.0001	0.0047
		(-0.01)	(0.05)
Predict. Time		-0.0049	-0.0243
		(-0.22)	(-0.24)
Predict. Cost		-0.0114	-0.0563
		(-0.66)	(-0.71)
Multiple Stops		0.0026	0.0124
		(0.21)	(0.22)
Min. Env. Impact		0.0072	0.0354
		(0.71)	(0.75)
Social Interaction		-0.0024	-0.0098
		(-0.36)	(-0.32)
Personality and risk variables			
BFI Extraversion		-0.0005	-0.0013
		(-0.03)	(-0.02)
BFI Agreeableness		0.0095	0.0449
		(0.37)	(0.38)
BFI Conscientiousness		0.0015	0.0119
		(0.06)	(0.11)
BFI Neuroticism		0.0044	0.0222
		(0.23)	(0.25)
BFI Openness		-0.0052	-0.0302
		(-0.25)	(-0.32)
Risk Averse ($1-20)		-0.1218**	-0.5723**
		(-2.48)	(-2.53)
Risk Averse ($30-40)		-0.0538	-0.2512
		(-1.23)	(-1.25)
Risk Loving ($60+)		-0.1405***	-0.6533***
		(-2.75)	(-2.81)
Constant	0.4482***	0.4693**	-0.1889
	(5.72)	(2.22)	(-0.19)
Observations	823	823	823
Adjusted R^2	0.11	0.11	
Observations Y=1	438	438	438

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. T-statistics

reported in parentheses. 'OLS' models report results generated using a linear probability model, while 'logit' results were produced using logistic regression. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when the respondent is interested in future adoption. The first OLS column of each section excludes $\mathbf{P'}_i$ variables described in Section 3 of the paper, while the remaining columns include both $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$.

Appendix Table D9: Omitting observations with NA responses for determinants of choice variables – Adopted and Interested in Adopting for Shared Services

	Adopted			**Interested in Adopting**		
	Ride-hail Single	Ride-hail Pooled	Car-Sharing	Ride-Hail Single	Ride-Hail Pooled	Car-Sharing
Born 1930s	0.2135	-0.0604	0.0051	0.3389	-0.1462	0.1230
Born 1940s	-0.0755	-0.0548	0.0018	0.0858	-0.0977	-0.0517
Born 1950s	-0.0201	-0.0529	0.0101	-0.0058	-0.0785	0.0077
Born 1970s	0.0594	-0.0107	-0.0024	0.0020	0.0042	-0.1048**
Born 1980s	0.1890***	0.1488***	0.0176	0.1105*	0.0591	-0.0809*
Born 1990s	0.2427***	0.2233***	0.0383	0.1209	0.0805	-0.0827
Any Child < 8yrs	-0.0426	-0.0622	0.0250	-0.0502	-0.0824*	0.0253
HH Income [75K,150K)	0.0465	0.0484	0.0169	0.0260	0.0035	0.0747*
HH Income [150K,200K)	0.0693	0.0499	0.0129	-0.0505	-0.0068	0.0681
HH Income ≥ 200K	0.1720***	0.0107	0.0358*	0.0159	-0.0075	0.0393
> 4yr College Ed.	0.0434	-0.0140	0.0167	0.0262	-0.0152	-0.0336
Female	-0.0091	-0.0051	-0.0124	-0.0233	-0.0475	-0.0613*
Res. Pop. Density	0.0007	0.0025	0.0003	-0.0016	-0.0024	0.0022
P.D. Pop. Density	-0.0006	0.0004	-0.0004	-0.0002	0.0000	-0.0004
Walk Score	0.0004	0.0006	0.0007**	0.0007	0.0015*	0.0008
Dist. to P.D. (10,20]	-0.0114	0.0104	-0.0059	0.1410***	0.0102	-0.0019
Dist. to P.D. (20,50]	-0.0021	-0.0374	0.0114	0.0417	-0.0565	-0.0342
Dist. to P.D. > 50mi	0.0925	0.0312	-0.0070	0.0045	0.0616	0.0421
Safety	0.0244	0.0000	0.0057	-0.0117	-0.0025	0.0032
Low Cost	-0.0196	-0.0039	-0.0008	-0.0338	-0.0002	0.0012
Low Hassle	-0.0143	-0.0104	-0.0173*	0.0082	0.0097	-0.0009
Short Time	0.0203	-0.0099	0.0061	0.0456*	0.0132	0.0065
Predict. Time	0.0071	-0.0025	0.0098	0.0093	-0.0030	-0.0467**
Predict. Cost	0.0002	0.0345**	-0.0019	-0.0124	-0.0095	0.0058
Multiple Stops	-0.0253*	-0.0136	0.0021	-0.0044	-0.0030	-0.0005
Min. Env. Impact	0.0245***	0.0130*	0.0015	-0.0009	0.0143*	0.0264***
Social Interaction	-0.0082	-0.0014	0.0010	-0.0100	-0.0072	0.0056
BFI-10: Extraversion	0.0421**	0.0369**	0.0094	0.0311	0.0252	-0.0062
BFI-10: Agreeableness	0.0173	0.0464**	-0.0021	0.0040	0.0110	0.0316
BFI-10: Conscientiousness	-0.0048	0.0007	-0.0044	-0.0150	0.0232	-0.0339
BFI-10: Neuroticism	-0.0061	-0.0018	-0.0060	-0.0043	0.0032	0.0104
BFI-10: Openness	0.0159	-0.0011	0.0044	0.0123	-0.0149	0.0357**
Risk Averse ($1-20)	0.0074	0.0034	0.0010	-0.1034*	-0.0500	0.0125
Risk Averse ($30-40)	-0.0263	-0.0194	-0.0127	-0.0263	0.0298	0.0802**
Risk Loving ($60+)	-0.0215	-0.0406	-0.0321**	-0.0014	-0.0562	-0.0114
Observations	770	770	770	546	630	748
Adjusted R^2	0.12	0.14	0.01	0.00	-0.00	0.04
Observations Y=1	224	140	22	158	135	153

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated

using a linear probability model and have included all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3 in the paper. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology or service. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when they report interest in future adoption. Constant is not reported.

Appendix Table D10: Omitting observations with NA responses for determinants of choice variables – Adopted and Interested in Adopting for Electrified Vehicle Technologies

	Adopted		**Interested in Adopting**	
	Hybrid	PEV	Hybrid	PEV
Born 1930s	-0.0884	-0.0847	0.0935	0.0464
Born 1940s	0.0388	0.0058	-0.0219	0.1373*
Born 1950s	0.1944***	-0.0261	0.0550	0.0941
Born 1970s	-0.0437	-0.0225	0.0239	0.0576
Born 1980s	-0.0688*	-0.0823***	0.0451	0.0774
Born 1990s	-0.0591	-0.0627*	0.1923**	0.0685
Any Child < 8yrs	-0.0012	0.0589*	-0.0067	-0.0225
HH Income [75K,150K)	0.0388	0.0008	0.0381	0.0369
HH Income [150K,200K)	0.0749*	0.0494*	-0.0985	0.1132*
HH Income ≥ 200K	0.1309***	0.0719**	-0.1138*	0.1265**
> 4yr College Ed.	0.0912***	0.0337*	0.0173	0.1053***
Female	0.0360	-0.0153	0.0360	-0.0932**
Res. Pop. Density	0.0009	0.0001	-0.0001	-0.0005
P.D. Pop. Density	-0.0016*	-0.0004	-0.0022	-0.0023*
Walk Score	0.0003	-0.0005	0.0009	0.0004
Dist. to P.D. (10,20]	0.0203	0.0335	-0.0093	0.0619
Dist. to P.D. (20,50]	0.0447	0.0361	0.0060	-0.0187
Dist. to P.D. > 50mi	-0.0452	0.0191	0.0293	0.0441
Safety	0.0073	-0.0017	-0.0284	-0.0354*
Low Cost	0.0148	0.0244**	0.0208	0.0153
Low Hassle	0.0231	-0.0211*	0.0077	0.0263
Short Time	-0.0296	0.0090	0.0352	0.0196
Predict. Time	-0.0391**	0.0088	0.0422	0.0297
Predict. Cost	0.0023	-0.0231*	-0.0311	-0.0409*
Multiple Stops	-0.0027	0.0011	-0.0217	-0.0303**
Min. Env. Impact	0.0002	0.0053	0.0204*	0.0412***
Social Interaction	-0.0001	0.0014	-0.0040	-0.0081
BFI-10: Extraversion	0.0026	-0.0087	-0.0398*	0.0186
BFI-10: Agreeableness	0.0189	0.0097	0.0349	0.0742***
BFI-10: Conscientiousness	-0.0297*	-0.0420***	0.0423	-0.0476*
BFI-10: Neuroticism	-0.0079	-0.0034	0.0062	0.0106
BFI-10: Openness	0.0192	0.0098	0.0215	0.0251
Risk Averse ($1-20)	-0.0094	-0.0542**	-0.0841	-0.0964*
Risk Averse ($30-40)	-0.0027	-0.0345	-0.0314	0.0242
Risk Loving ($60+)	0.0269	-0.0436	-0.1250**	-0.1403**
Observations	770	770	652	718
Adjusted R^2	0.08	0.05	0.04	0.08
Observations Y=1	118	52	280	397

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated using a linear probability model and have included all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3 in the paper. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology or service. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when they report

interest in future adoption. Constant is not reported.

Appendix Table D11: Omitting observations with NA responses for determinants of choice variables – Adopted and Interested in Adopting Automated Vehicle Technologies

	Adopted		Interested in Adopting		
	Adaptive Cruise Control	Partially Automated	Adaptive Cruise Control	Partially Automated	Fully Automated
Born 1930s	0.1315	0.2929	0.1914	0.3735	0.2755
Born 1940s	0.0040	0.0239	0.0877	0.2039**	0.0335
Born 1950s	-0.1062**	-0.0324	0.0792	0.0771	-0.0199
Born 1970s	-0.0425	0.0072	0.0532	0.0673	-0.0545
Born 1980s	-0.0130	0.0011	0.0363	0.0833	0.0370
Born 1990s	-0.0741	-0.0170	0.1405*	0.2399***	0.2093***
Any Child < 8yrs	0.0228	-0.0140	-0.0815	-0.0366	0.0196
HH Income [75K,150K)	0.0375	0.0107	0.0511	0.0672	0.1069**
HH Income [150K,200K)	0.0529	0.0020	0.1435**	0.0720	0.1225**
HH Income ≥ 200K	0.1097***	0.0381*	0.1465**	0.1631***	0.1868***
> 4yr College Ed.	0.0251	0.0047	0.0419	0.0227	0.0377
Female	-0.0127	-0.0252	-0.1518***	-0.1566***	-0.2544***
Res. Pop. Density	-0.0007	0.0006	-0.0005	0.0004	-0.0020
P.D. Pop. Density	-0.0010	0.0001	0.0017	0.0003	0.0018
Walk Score	0.0007	-0.0001	-0.0008	-0.0010	0.0002
Dist. to P.D. (10,20]	-0.0079	0.0264	0.0180	0.0075	-0.0053
Dist. to P.D. (20,50]	-0.0092	-0.0021	0.0258	0.0038	-0.0293
Dist. to P.D. > 50mi	-0.0048	-0.0313	0.0202	0.0301	-0.0399
Safety	-0.0014	-0.0122	-0.0166	-0.0195	0.0021
Low Cost	-0.0081	0.0137	-0.0177	-0.0191	-0.0177
Low Hassle	0.0124	0.0134	-0.0170	0.0196	0.0143
Short Time	0.0230	-0.0061	0.0117	0.0224	0.0202
Predict. Time	-0.0101	-0.0002	0.0031	0.0003	0.0041
Predict. Cost	0.0098	-0.0081	-0.0191	-0.0050	-0.0055
Multiple Stops	0.0125	0.0051	-0.0126	-0.0157	-0.0091
Min. Env. Impact	-0.0234**	-0.0123**	0.0229*	0.0246**	0.0091
Social Interaction	0.0027	0.0014	-0.0171**	-0.0041	-0.0007
BFI-10: Extraversion	-0.0031	-0.0002	0.0120	0.0261	0.0069
BFI-10: Agreeableness	0.0443**	0.0019	0.0013	0.0083	0.0057
BFI-10: Conscientiousness	0.0171	0.0117	0.0292	-0.0180	-0.0099
BFI-10: Neuroticism	0.0056	0.0020	0.0137	0.0056	0.0004
BFI-10: Openness	0.0052	0.0039	-0.0048	-0.0099	-0.0020
Risk Averse ($1-20)	-0.0576	-0.0345*	-0.0488	-0.1440***	-0.1288**
Risk Averse ($30-40)	-0.0154	-0.0315	-0.1021*	-0.0979**	-0.0612
Risk Loving ($60+)	0.1195**	0.0075	-0.1067*	-0.0763	-0.1296**
Observations	770	770	637	738	767
Adjusted R^2	0.03	0.01	0.04	0.06	0.10
Observations Y=1	133	32	302	357	412

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated using a linear probability model and have included all $\mathbf{X}'_{igc}$ and $\mathbf{P}'_{i}$ variables and county fixed effects described in Section 3 in the paper. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology or service. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when they report interest in future adoption. Constant is not reported.

Appendix Table D12: When NA responses for determinants of choice variables are replaced with the value 3 – Adopted and Interested in Adopting Shared Services

	Adopted			Interested in Adopting		
	Ride-hail Single	Ride-hail Pooled	Car-Sharing	Ride-hail Single	Ride-hail Pooled	Car-Sharing
Born 1930s	0.1306	0.0844	0.0198	0.1189	-0.1510**	-0.1462
Born 1940s	-0.0715	-0.0503	0.0027	0.0877	-0.0954	-0.0587
Born 1950s	-0.0088	-0.0433	0.0126	-0.0235	-0.0580	-0.0088
Born 1970s	0.0591	0.0006	-0.0024	-0.0098	0.0054	-0.1186**
Born 1980s	0.1995***	0.1631***	0.0156	0.0963	0.0715	-0.0992**
Born 1990s	0.2509***	0.2340***	0.0368	0.1373*	0.1003	-0.0831
Any Child < 8yrs	-0.0489	-0.0602	0.0242	-0.0624	-0.0857*	0.0243
HH Income [75K,150K)	0.0311	0.0579*	0.0139	0.0352	0.0063	0.0808**
HH Income [150K,200K)	0.0614	0.0583	0.0119	-0.0491	0.0050	0.0739
HH Income ≥ 200K	0.1723***	0.0241	0.0328*	0.0252	-0.0049	0.0338
> 4yr College Ed.	0.0378	-0.0125	0.0163	0.0205	-0.0189	-0.0457
Female	0.0112	0.0002	-0.0117	-0.0240	-0.0404	-0.0642**
Res. Pop. Density	0.0006	0.0024	0.0004	-0.0019	-0.0027	0.0021
P.D. Pop. Density	-0.0007	0.0003	-0.0004	0.0001	0.0002	-0.0003
Walk Score	0.0005	0.0007	0.0006**	0.0007	0.0017**	0.0008
Dist. to P.D. (10,20]	-0.0055	0.0052	-0.0047	0.1479***	0.0036	0.0044
Dist. to P.D. (20,50]	0.0231	-0.0327	0.0102	0.0454	-0.0656	-0.0434
Dist. to P.D. > 50mi	0.0532	0.0102	-0.0096	0.0302	0.0282	0.0164
Safety	0.0233	-0.0008	0.0064	-0.0123	-0.0042	0.0034
Low Cost	-0.0188	-0.0034	-0.0008	-0.0370	0.0008	0.0009
Low Hassle	-0.0146	-0.0085	-0.0161*	0.0046	0.0081	-0.0032
Short Time	0.0213	-0.0133	0.0078	0.0494*	0.0115	0.0088
Predict. Time	0.0064	-0.0020	0.0118*	0.0059	-0.0049	-0.0465**
Predict. Cost	-0.0017	0.0349**	-0.0024	-0.0119	-0.0096	0.0049
Multiple Stops	-0.0259**	-0.0142	0.0011	-0.0005	-0.0032	0.0016
Min. Env. Impact	0.0239***	0.0128*	0.0018	-0.0009	0.0146*	0.0251***
Social Interaction	-0.0051	-0.0007	0.0012	-0.0085	-0.0075	0.0069
BFI-10: Extraversion	0.0443***	0.0447***	0.0077	0.0257	0.0241	-0.0117
BFI-10: Agreeableness	0.0198	0.0469**	-0.0033	-0.0092	0.0185	0.0369*
BFI-10: Conscientiousness	-0.0144	-0.0012	-0.0043	-0.0182	0.0086	-0.0351*
BFI-10: Neuroticism	-0.0018	0.0018	-0.0060	-0.0137	0.0065	0.0029
BFI-10: Openness	0.0166	-0.0043	0.0045	0.0132	-0.0184	0.0332*
Risk Averse ($1-20)	-0.0093	-0.0041	0.0005	-0.0824	-0.0471	-0.0062
Risk Averse ($30-40)	-0.0424	-0.0322	-0.0119	-0.0145	0.0375	0.0569
Risk Loving ($60+)	-0.0298	-0.0517	-0.0291**	-0.0059	-0.0456	-0.0346
Observations	826	826	826	587	675	804
Adjusted R^2	0.12	0.15	0.02	0.01	0.01	0.05
Observations Y=1	239	151	22	170	145	167

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated using a linear probability model and have included all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3 in the paper. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology or service. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when they report interest in future adoption. Constant is not reported.

Appendix Table D13: When NA responses for determinants of choice variables are replaced with the value 3 – Adopted and Interested in Adopting Electrified Vehicle Technologies

	Adopted		Interested in Adopting	
	Hybrid	PEV	Hybrid	PEV
Born 1930s	-0.0574	0.0083	0.1586	0.0247
Born 1940s	0.0576	0.0078	-0.0557	0.1440*
Born 1950s	0.1626***	-0.0259	0.0475	0.1028
Born 1970s	-0.0645	-0.0235	0.0105	0.0603
Born 1980s	-0.0940**	-0.0835***	0.0400	0.0614
Born 1990s	-0.0803*	-0.0644**	0.1880***	0.0792
Any Child < 8yrs	-0.0037	0.0569*	-0.0103	-0.0164
HH Income [75K,150K)	0.0545*	-0.0002	0.0213	0.0332
HH Income [150K,200K)	0.0841**	0.0467*	-0.1216*	0.0820
HH Income ≥ 200K	0.1316***	0.0740**	-0.1583***	0.0928
> 4yr College Ed.	0.0933***	0.0298	0.0241	0.0974**
Female	0.0382	-0.0102	0.0334	-0.0985**
Res. Pop. Density	0.0010	-0.0000	-0.0004	-0.0002
P.D. Pop. Density	-0.0015*	-0.0003	-0.0021	-0.0020
Walk Score	0.0003	-0.0005	0.0011	0.0004
Dist. to P.D. (10,20]	0.0081	0.0325	0.0099	0.0779*
Dist. to P.D. (20,50]	0.0455	0.0426	0.0227	-0.0218
Dist. to P.D. > 50mi	-0.0529	0.0255	-0.0172	-0.0178
Safety	0.0023	-0.0040	-0.0130	-0.0162
Low Cost	0.0036	0.0261***	0.0130	0.0063
Low Hassle	0.0185	-0.0236**	0.0149	0.0137
Short Time	-0.0209	0.0047	0.0414*	0.0412*
Predict. Time	-0.0258	0.0130	0.0105	0.0068
Predict. Cost	0.0066	-0.0208**	-0.0423**	-0.0281
Multiple Stops	-0.0071	0.0032	-0.0198	-0.0352***
Min. Env. Impact	-0.0012	0.0055	0.0192*	0.0368***
Social Interaction	0.0003	0.0015	-0.0046	-0.0098
BFI-10: Extraversion	-0.0048	-0.0116	-0.0418**	0.0052
BFI-10: Agreeableness	0.0220	0.0096	0.0240	0.0652**
BFI-10: Conscientiousness	-0.0325**	-0.0408***	0.0390	-0.0453*
BFI-10: Neuroticism	-0.0122	-0.0038	0.0004	0.0019
BFI-10: Openness	0.0102	0.0059	0.0253	0.0259
Risk Averse ($1-20)	0.0026	-0.0421*	-0.0899*	-0.0772
Risk Averse ($30-40)	-0.0050	-0.0329	-0.0321	0.0200
Risk Loving ($60+)	0.0394	-0.0467*	-0.1400**	-0.1561***
Observations	826	826	699	772
Adjusted R^2	0.07	0.06	0.05	0.07
Observations Y=1	127	54	306	426

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated using a linear probability model and have included all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_i$ variables and county fixed effects described in Section 3 in the paper. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology or service. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when they report interest in future adoption. Constant is not reported.

Appendix Table D14: When NA responses for determinants of choice variables are replaced with the value 3 – Adopted and Interested in Adopting Automated Vehicle Technologies

	Adopted		Interested in Adopting		
	Adaptive Cruise Control	Partially Automated	Adaptive Cruise Control	Partially Automated	Fully Automated
Born 1930s	-0.0414	0.0651	0.0233	0.1270	0.1024
Born 1940s	0.0271	0.0269	0.0698	0.2159***	0.0491
Born 1950s	-0.0960**	-0.0300	0.0647	0.0615	0.0076
Born 1970s	-0.0305	0.0169	0.0167	0.0511	-0.0554
Born 1980s	-0.0160	0.0059	0.0046	0.0637	0.0497
Born 1990s	-0.0706	-0.0115	0.1043	0.2218***	0.2297***
Any Child < 8yrs	0.0356	-0.0180	-0.0739	-0.0425	0.0351
HH Income [75K,150K)	0.0427	0.0089	0.0487	0.0686	0.1083**
HH Income [150K,200K)	0.0513	0.0024	0.1128*	0.0567	0.1186**
HH Income ≥ 200K	0.1131***	0.0434**	0.1115*	0.1502***	0.1934***
> 4yr College Ed.	0.0255	0.0034	0.0458	0.0260	0.0341
Female	-0.0070	-0.0273*	-0.1576***	-0.1579***	-0.2600***
Res. Pop. Density	-0.0008	0.0005	-0.0002	0.0004	-0.0020
P.D. Pop. Density	-0.0011	0.0000	0.0015	-0.0001	0.0018
Walk Score	0.0008	-0.0001	-0.0006	-0.0008	0.0003
Dist. to P.D. (10,20]	-0.0028	0.0291	0.0509	0.0322	0.0085
Dist. to P.D. (20,50]	-0.0028	-0.0038	0.0355	0.0128	-0.0177
Dist. to P.D. > 50mi	-0.0240	-0.0264	-0.0056	-0.0231	-0.0430
Safety	-0.0054	-0.0126	-0.0059	-0.0244	0.0036
Low Cost	-0.0033	0.0114	-0.0135	-0.0164	-0.0063
Low Hassle	0.0151	0.0082	-0.0157	0.0068	0.0173
Short Time	0.0227	-0.0023	0.0188	0.0276	-0.0001
Predict. Time	-0.0146	-0.0021	0.0040	0.0027	-0.0049
Predict. Cost	0.0169	-0.0014	-0.0212	-0.0022	-0.0114
Multiple Stops	0.0130	0.0086	-0.0154	-0.0077	0.0026
Min. Env. Impact	-0.0242***	-0.0122**	0.0188	0.0203*	0.0072
Social Interaction	0.0019	0.0012	-0.0168**	-0.0038	-0.0024
BFI-10: Extraversion	-0.0053	-0.0020	0.0151	0.0183	-0.0005
BFI-10: Agreeableness	0.0448**	0.0048	-0.0017	0.0057	0.0095
BFI-10: Conscientiousness	0.0149	0.0111	0.0251	-0.0151	0.0015
BFI-10: Neuroticism	0.0011	0.0011	0.0080	-0.0002	0.0044
BFI-10: Openness	0.0024	0.0026	-0.0040	-0.0090	-0.0052
Risk Averse ($1-20)	-0.0471	-0.0232	-0.0628	-0.1470***	-0.1218**
Risk Averse ($30-40)	-0.0093	-0.0295	-0.1060**	-0.1003**	-0.0538
Risk Loving ($60+)	0.1254***	0.0065	-0.1198*	-0.1002*	-0.1405***
Observations	826	826	688	793	823
Adjusted R^2	0.04	0.01	0.03	0.06	0.11
Observations Y=1	138	33	329	384	438

* p<0.10, ** p<0.05, *** p<0.01 report statistical significance for robust standard errors. Results were generated

using a linear probability model and have included all $\mathbf{X'}_{igc}$ and $\mathbf{P'}_{i}$ variables and county fixed effects described in Section 3 in the paper. The dependent variable = 1 in 'Adopted' models when the respondent has adopted the technology or service. 'Interested in Adopting' uses the subsample that has not yet adopted, and =1 when they report interest in future adoption. Constant is not reported.

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