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Shared autonomous vehicles and their potential impacts on household vehicle ownership: An exploratory empirical assessment

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ABSTRACT

Emerging transportation technologies have the potential to significantly reshape the transportation systems and household vehicle ownership. Key among these transportation technologies are the autonomous vehicles, particularly when introduced in shared vehicle fleets. In this paper, we focus on the potential impact that fleets of shared autonomous vehicles might have on household vehicle ownership. To obtain initial insights into this issue, we asked a sample of university personnel and members of the American Automobile Association as to how likely they would consider relinquishing one of their household's personal vehicles if shared autonomous vehicles were available (thus reducing their household vehicle ownership level by one). For single-vehicle households, this would be relinquishing their only vehicle, and for multivehicle households (households owning two or more vehicles) this would be relinquishing just one of their vehicles. Possible responses to the question about relinquishing a household vehicle if shared autonomous vehicles are present are: extremely unlikely, unlikely, unsure, likely, and extremely likely. To determine the factors that influence this response, random parameters ordered probit models are estimated to account for the likelihood that considerable unobserved heterogeneity is likely to be present in the data. The findings show that a wide range of socioeconomic factors affects people's likelihood of vehicle relinquishment in the presence of shared autonomous vehicles. Key among these are gender effects, generational elements, commuting patterns, and respondents' vehicle crash history and experiences. While people's opinions of shared autonomous vehicles are evolving with the continual introduction of new autonomous vehicle technologies and shifting travel behavior, the results of this study provide important initial insights into the likely effects of shared autonomous vehicles on household vehicle ownership.

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1. Introduction

Emerging automotive and transportation technologies, such as autonomous vehicles (AVs), have created revolutionary possibilities with regard to future travel. Several prominent automotive and technology companies have presented their versions of AVs, and are predicting that AV technology, with the capability of being fully self-driving, will be available to the general public in the near future (Fagnant and Kockelman, 2015a; Menon, Pinjari, Zhang, & Zou, 2016). With fully self-driven vehicles, users may not need to be engaged in the driving process and could, therefore, be involved a host of other activities, such as working, talking to friends, sleeping, or reading (Le Vine, Zolfaghari, & Polak, 2015).

As the technological development is progressing rapidly, governmental agencies are grappling with how to plan transportation systems for such technologies. Considering the high initial cost of owning these technologies, there is a significant discussion on the possible emergence of shared autonomous vehicle (SAV) fleets as an alternative to owning individual AVs.

Testing of SAVs has gathered momentum, with Uber, nuTonomy, and Lyft evaluating these technologies on city streets (Bliss, 2016; Boston, 2017). Waymo, Alphabet's subsidiary AV business, purchased thousands of Chrysler Pacifica Hybrids at the beginning of 2018. These vehicles will join the AV fleet that is already running in Waymo's test cities. Waymo will use this expanded fleet to provide SAV service to users, which is called the Early Rider program (Caughill, 2018). Additionally, the entry of innovative transit companies, such as Navya and EasyMile, into college campuses and cities, for testing and research purposes, is further evidence of the growing interest in SAVs (Hawkins, 2017; Motion Digest, 2017). SAVs have the potential to be an inexpensive on-demand mobility service that could play a key role in the future transportation systems. For instance, SAVs could provide convenient last-mile (transporting people from transit drop-offs to final destinations) solutions to support multimodal transportation systems (Krueger, Rashidi, & Rose, 2016). In fact, recent literature, modeling different scenarios with SAV fleets, show significant

cost benefits in comparison to individually owned and operated vehicles (Fagnant and Kockelman, 2015a).

Past studies on understanding household vehicle ownership trends have provided interesting insights on what triggers the acquisition as well as the relinquishment of vehicles. There has been a downward trend in vehicle purchases over the last few years among younger generations (Millard-Ball & Schipper, 2011) and, over the years, the influence of life events on household vehicle relinquishments has been well documented (Clark, Chatterjee, & Melia, 2015; Dargay & Hanly, 2007; Oakil, Ettema, Arentze, & Timmermans, 2014; Rashidi & Mohammadian, 2016). Even without automation, there is increasing evidence that the emergence of vehicle-sharing services is leading to a reduction in household vehicle ownership (Martin, Shaheen, & Lidicker, 2010; Elliott and Shaheen, 2011). For instance, individuals who currently own vehicles out of necessity, rather than preference, are likely to switch to vehicle-sharing (Ohta, Fujii, Nishimura, & Kozuka, 2013), if provided at a cost comparable to owning a personal vehicle. There is an increasing possibility of higher levels of vehicle relinquishment at the household level when technologies take the task of driving away from the driver.

Recent news on the emergence of popular vehicle-sharing services, such as Uber and Lyft (Kosoff, 2016), have supported the need to understand possible shifts in household vehicle ownership trends with the introduction of SAVs. While a relatively large number of previous studies have focused on understanding people's preferences for AVs and their intended adoption (Menon et al., 2016; Schoettle & Sivak, 2014), only a few studies have explicitly dealt with the adoption of SAVs. Examples include Haboucha, Ishaq, and Shiftan (2015), who conducted a stated preference questionnaire among 800 individuals living in Israel and North America to develop a joint ownership and choice model that included shifting to a fleet of SAVs among other options (retain vehicle, buy and ride in an autonomous vehicle), and Bansal, Kockelman, and Singh (2016), who analyzed individuals' frequency of use of SAVs under different pricing scenarios and identified characteristics of potential SAV users. Furthermore, studies generally do not explicitly address households' tendency to relinquish vehicles in the presence of SAVs. Yet, people's willingness to relinquish household vehicles in the presence of SAVs is a key to the success of SAV systems. Therefore, the objective of this study is to understand the factors influencing households' intentions to relinquish their own vehicles in the presence of SAVs.

To this end, we conduct a survey of two different target groups of interest: faculty, students, and staff from a large university (University of South Florida); and the members of the American Automobile Association (AAA) Foundation of the southeastern United States. We develop a survey instrument asking them how likely they would be to consider relinquishing one of their household's personal vehicles if SAVs were available (thus reducing their household vehicle ownership level by one). University members were chosen because universities are often a fertile ground for testing and early adoption of new technologies. Additionally, university respondents are often some of the earliest adopters (and sometimes vocal critics) of emerging

technologies, thereby making them an interesting demographic to consider for the purpose of our study. Also, with approximately every one in four households in the United States being AAA members (American Automobile Association, 2017), the results from this study would be representative of a broad cross-section of American society. However, it is important to note that the intent of our study is exploratory and, as such, we do not seek a nationally representative sample. In a time when opinions and attitudes toward AVs are changing rapidly as technologies advance and consumers process available information, even a fully representative national sample would provide findings that would not be temporally stable. Thus our focus on a select subsample of potential consumers is intended to provide some initial insights and a demonstration of a methodological approach that can be used to guide future studies on the subject.

Possible responses to the question of interest relating consumer intentions to relinquish their own vehicles in the presence of SAVs are: extremely unlikely, unlikely, unsure, likely, and extremely likely. For single-vehicle households, this would be relinquishing their only vehicle, and for multivehicle households (households owning two or more vehicles) this would be relinquishing one of their vehicles. Therefore, two different random parameters ordered probit models are estimated to analyze the factors that influence the households' likelihood of relinquishing one of their vehicles; one model for single-vehicle households and the other model for multivehicle households. While people's opinions of SAVs will likely evolve (as well as fluctuate) with the increasing penetration of new AV technologies and the realization of their benefits (or negative impacts), the model results provide important initial insights into the likely effects of SAVs on household vehicle ownership in the short term.

The remainder of our paper starts, in Section 2, with an assessment of recent trends in vehicle acquisition and relinquishment and goes on, in Section 3, to a discussion of ideas relating to SAVs and their potential impacts on vehicle ownership. Section 4 describes the data used for the analysis. Section 5 presents the random parameters ordered probit modeling methodology used to study possible household vehicle relinquishment. Section 6 discusses the statistical results, and Section 7 deliberates their implications for vehicle ownership (vehicle relinquishment, to be precise) in a SAV environment. Section 8 concludes the paper.

2. Vehicle ownership trends

Since the turn of the millennium, vehicle ownership levels have seen a steady decline among the young (Kuhnimhof, Zumkeller, & Chlond, 2013; Metz, 2013; Millard-Ball & Schipper, 2011). Recent studies have shown that this growing trend among millennials (those who are born in the 1980s and 1990s) would make them own fewer vehicles, drive less and be less likely to obtain driving licenses (Polzin, Chu, & Godfrey, 2014). The reasons for this decline in vehicle purchases have been attributed to many factors including changing preferences in urban living, increased transit use, increased environmental awareness, and shifting economic circumstances (McDonald, 2015; van Wee, 2015). While several studies have pointed to the role of new technologies in reducing travel

(Martin et al., 2010) and therefore a decline in vehicle ownership levels (van Wee, 2015), others take the more skeptical view that new technologies can often create new travel demand and more travel, not less (Blumenberg et al., 2012; Mokhtarian, 2002, 2009).

Past research has shown that the acquisition and relinquishment of motorized vehicles is a complex intertemporal decision-making process (Mannering & Winston, 1985), and can often be the result of a life-changing event that typically leads to changes in travel behavior and vehicle utilization (Beige & Axhausen, 2012; Chatterjee, Sherwin, & Jain, 2013; Clark et al., 2015; Dargay & Hanly, 2007). As an example, Oakil et al. (2014) examined households in the Netherlands and found an association between vehicle relinquishments and childbirth in households. Another study by Zhang, Yu, and Chikaraishi (2014), conducted in Japan, shows how vehicle ownership changes are influenced by residential moves than by changes in education or employment. Other studies show the complex influence of household-level changes (job relocation of family members, presence of children, household member(s) leaving the household, and so on) and travel attributes on the decision of buying and selling vehicles (Rashidi, Mohammadian, & Koppelman, 2011).

The precise timing of vehicle transactions (acquisition and relinquishment) has also been identified as a critical concern in the literature. Early work by Mannering and Winston (1991) estimated a hazard-based Weibull duration model to study the time between vehicle acquisitions and, in subsequent work, Rashidi and Mohammadian (2016) applied a competing duration risk model to study the dynamics of transaction timing by vehicle transaction type (acquisition, trade, and disposal), which allowed them to explicitly capture the timing interactions among the various transaction types. These empirical duration-model approaches have provided valuable insights into the factors that affect the timing of vehicle-transaction decisions, which will play a critical role in the timing of the adoption of SAVs.

3. Vehicle ownership in the presence of SAVs

Vehicle-sharing is considered a flexible mobility option that offers the flexibility of a private vehicle without the responsibilities associated with private vehicle ownership (Shaheen & Cohen, 2013). The potential benefits envisioned with vehicle-sharing include the facilitation of multimodal travel behavior (Nobis, 2006) and eventually the reduction in vehicle ownership levels (Firnkorner & Muller, 2012; Martin et al., 2010).

Vehicle-sharing with AVs has the potential to revolutionize travel with respect to conventional vehicle-sharing, ride-sharing, and ride-sourcing (for hire vehicle with a single passenger) paradigms. Because SAVs will be able to drive up to potential passengers, walking times to access shared vehicles could potentially be reduced to near zero. Conventional vehicle-sharing has suffered from availability concerns for one-way vehicle-sharing users because there may not always be a vehicle available for use at the destination once travelers finish their activity. Thus, conventional vehicle sharing requires substantial labor costs to rebalance the potential mismatch of supply and demand. An SAV-based vehicle-sharing model has the

potential to avoid such issues (Fagnant & Kockelman, 2014; Firnkorn & Muller, 2015).

On-demand mobility service with an SAV fleet could alleviate many of the adverse environmental impacts of current on-demand mobility services with human-driven vehicles. For example, a recent simulation-based study of an SAV fleet in Austin, Texas, (Fagnant & Kockelman, 2015b) showed that the excess vehicle kilometers traveled due to empty vehicle relocation could be reduced by almost 50% with SAV on-demand mobility service relative to current, conventional on-demand mobility services. In addition, implementing on-demand mobility services with the use of SAVs would eliminate the transaction costs involved with having a driver operate the vehicle from origin to destination (Krueger et al., 2016).

While there is ample literature on the potential users of AVs, there is substantially less information on potential user groups when it comes to SAVs. Past research points toward SAVs becoming an attractive mobility option for subgroups of the population such as the elderly or individuals who are currently unwilling and/or unable to drive (Alsnih & Hensher, 2003; Rosenbloom, 2001; Fagnant and Kockelman, 2015a; Shaheen, Cano, & Camel, 2016). For example, research by Sikder and Pinjari (2012) found that while elderly may become immobile due to physical and cognitive limitations, their desire to continue to be mobile remains. Thus, SAVs could act as an elderly mobility alternative with the possibility of providing convenient and flexible mobility at a lower cost without the burden of driving. It should be pointed out, however, that it has been shown that population subgroups such as elderly cohorts are highly heterogeneous and vary considerably with respect to their motives for travel and the use of different modes (Haustein, 2012). In addition to the elderly, SAVs could be thought of as an age-appropriate mobility alternative for travelers who do not have access to private transportation, regardless of their age (Anderson et al., 2014; Krueger et al., 2016).

There is very little academic literature on the impact of SAVs on future household vehicle ownership trends in terms of both acquisitions and relinquishments, although recent discussions on potential vehicle ownership impacts have been fueled by the investment of transportation network companies (TNCs), like Uber and Lyft, in the AV market. With regard to the impacts of the emerging SAV business models on future vehicle ownership, Lyft predicts that vehicle ownership will all but end by 2025 (Kosoff, 2016), and Jaynes (2016) provides a comprehensive discussion on this topic by explaining the various scenarios that may arise regarding vehicle ownership in a driverless era. For example, Jaynes argues that it is very likely that the ownership model will never change for luxury vehicle buyers. However, it seems likely that luxury vehicle brands may start offering different ownership programs to cater to a driverless world, besides the traditional model of full ownership, with a more flexible fractional ownership model where the people pay a price depending on their usage. Other possible models of ownership that would arise in a driverless world with SAVs could include an own-plus-share model where people could still be tied to the traditional vehicle ownership but be able to opt into a sharing program where their vehicles would autonomously drive and chauffeur people around during its idle time (Jaynes, 2016).

From a market impact perspective, a number of studies have found that SAVs have the potential to displace conventional vehicles (Fagnant & Kockelman, 2014; Spieser et al., 2014; Wang, Yang, & Yang, 2006), but the magnitude of this displacement has been estimated to vary widely and is not well understood. Still, individuals' willingness to relinquish their conventional household vehicles in the presence of available SAVs is critical to measuring the impact and success of SAVs.

Given the above discussions, it is clear that future household vehicle ownership decisions in the presence of SAVs are going to be complex and involve individual perceptions with regard to technology, potential benefits, likely costs, and so on. The objective of the current paper is to develop some insights into these decisions by studying the willingness of people to relinquish a currently held household vehicle when SAVs become available.

4. Data

To understand the factors that may influence people's willingness to relinquish a household-owned vehicle in the presence of SAVs (thus reducing their household vehicle ownership level by one), a web-based survey was conducted to target population groups. The first targeted group is the students, faculty, and staff of the University of South Florida (USF) system (all three campuses: Tampa, St. Petersburg, and Sarasota-Manatee), and the second targeted group is members of American Automobile Association (AAA) South. The customized surveys consisting of 94 (USF) and 75 questions (AAA) were disseminated for data collection during April and June 2015, respectively. Some university-related questions, such as working status at university, international students, on-campus residence, university campus, were removed in AAA survey questionnaire. Meanwhile, additional questions on number of children in the household, and when the most severe crash occurred, were added into the AAA questionnaire at the request of AAA personnel (for the analysis of travel-related matters of interest to their association).

Part A of the survey collected general information including respondent demographics, current travel characteristics, crash history, and vehicle inventories. Part B elicited information on consumers' perceptions of AVs. Questions included respondent familiarity with AVs, likelihood of certain benefits and concerns with AVs, willingness to pay and use AVs, understanding of on-board safety/automation features. The last part of the multipopulation surveys gathered information on the anticipated travel-related impacts of AVs, including individuals' willingness to use shared autonomous modes for their trips. Part C also collected information relating to people's willingness to relinquish one of their household vehicles, given the availability of SAVs.

The willingness to relinquish a vehicle in the presence of SAVs presents respondents with a difficult hypothetical choice. First, individuals do not currently have a good grasp of AV technology and its operational characteristics in a shared environment. Second, because household vehicle decisions involve a complex intertemporal decision-making process that includes number of vehicles, type of vehicles, individual vehicle utilizations, intertemporal discounting, etc. (Manning & Winston,

1985), the willingness to relinquish will have a temporal dynamic that will be impossible to completely capture in a hypothetical survey (Rashidi & Mohammadian, 2016). And third, there is ample evidence from fields such as psychology, neuroscience, economics, and cognitive science that suggests that the introduction of a new choice option (such as SAVs) will result in an extended period where individual preferences will be highly unstable as they gather information, develop attitudes, potentially polarize in their preferences, etc. (Manning, 2018). Because it is virtually impossible to account for the above factors in hypothetical choices of SAV preferences, our forthcoming analysis will be limited in this regard. However, even with these limitations, our analysis will provide some potentially important initial insights into individual preferences for SAVs.

Using data collected from both the target groups, a total of 1214 observations were available to study people's willingness to relinquish their household vehicles in the presence of SAVs (for the 417 single-vehicle households, this would be relinquishing their only vehicle, for the 797 multivehicle households, households owning two or more vehicles, this would be relinquishing just one of their vehicles). At the time the survey was conducted, and even today, the exact specifications and attributes of SAV systems are not yet fully known or understood. Therefore, a stated preference survey about hypothetical scenarios would be saddled with a hypothetical bias as has been found in previous literature (Carlsson, 2010; Chang, Lusk, & Norwood, 2009). In light of this, the approach we adopt (one without a stated preferences and the additional details of a SAV system) still provides important initial insights into respondent intentions for relinquishing one household vehicle and partaking in a shared-vehicle environment.

In our data, 27.5% of respondents indicated their likelihood of relinquishing a household vehicle in the presence of SAVs as extremely unlikely, 26.7% as unlikely, 19.4% as unsure, 18.6% as likely, and 7.3% as extremely likely. Table 1 provides summary statistics for some key elements of the sample. This table shows that roughly one-fifth of those surveyed were millennials (20.7%) and that 37.1% of the respondents possessed a graduate degree. Nearly one-fourth of the respondents belonged to households with an annual income below \$50,000 (24.1%) and traveled a one-way commute distance of fewer than 10 miles (25.8%). However, a majority of the respondent households owned multiple vehicles (65.7%) and had been involved in a crash prior to taking the survey (74%).

5. Methodology

Several statistical/econometric modeling approaches are available to capture the influence of multiple factors that may affect vehicle ownership decisions in the presence of SAVs. In the current study, we will estimate a random parameter ordered probit model where the dependent variable (people's willingness to relinquish a household vehicle, thus reducing their household vehicle ownership level by one, in the presence of SAVs) is modeled as ordinal data (where respondents indicate their willingness to relinquish as extremely unlikely, unlikely, unsure, likely, or extremely likely).

Table 1. Descriptive statistics of the variables of interest in understanding respondent's willingness to relinquish a household vehicle with the introduction of shared autonomous vehicles for single-vehicle households (multivehicle household values in parentheses).

Variable description	Descriptive statistics	
	Mean	Standard deviation
Male respondent indicator (1 if respondent is male, 0 otherwise)	0.420 (0.605)	0.494 (0.489)
Millennial indicator (1 if respondent is classified as a millennial, 0 otherwise)	0.393 (0.109)	0.489 (0.312)
White respondent Indicator (1 if respondent is classified as white, 0 otherwise)	0.822 (0.866)	0.383 (0.341)
Post Graduate indicator (1 if respondent's highest educational qualification is a post graduate degree, 0 otherwise)	0.372 (0.371)	0.484 (0.483)
Multiperson household indicator ((1 if respondent is a member of a household with more than 3 persons, 0 otherwise)	0.086 (0.252)	0.281 (0.435)
Single licensed driver household indicator (1 if respondent is a member of a household with only one licensed driver, 0 otherwise)	0.465 (0.080)	0.499 (0.266)
Vehicle ownership indicator (1 if respondents is a member of a household that owns three or more vehicles, 0 otherwise)	– (0.407)	– (0.491)
Moderate commute distance indicator (1 if respondent travels a one-way distance less than 10 miles for their commute, 0 otherwise)	0.348 (0.211)	0.477 (0.408)
High daily travel time indicator (1 if respondent travels more than 90 minutes every day for all their trips, 0 otherwise)	0.158 (0.156)	0.365 (0.363)
Low parking time indicator (1 if respondent spends 5 minutes or less in order to park their vehicle, 0 otherwise)	0.465 (0.650)	0.499 (0.477)
Crash indicator (1 if respondent has been involved in a traffic crash in the past, 0 otherwise)	0.688 (0.766)	0.464 (0.423)
Complete vehicle damage indicator (1 if respondent was in a crash that resulted in their vehicles suffering complete damage, totaled, 0 otherwise)	0.216 (0.231)	0.412 (0.422)
No injury severity indicator (1 if the respondent was involved in one or more crashes, but no respondent-involved crashes resulted in injury, 0 otherwise)	0.676 (0.640)	0.468 (0.480)

With such ordered data (extremely unlikely, unlikely, unsure, likely, extremely likely to relinquish), an ordered probability modeling approach is appropriate (Greene, 1997; Washington, Karlaftis, & Mannering, 2011). An ordered probability model is derived by defining an unobserved variable, z , which is used as a basis for modeling the ordinal ranking of data. This unobserved variable is specified as a linear function

$$z_n = \beta X_n + \varepsilon_n \quad (1)$$

where \mathbf{X} is a vector of explanatory variables determining the discrete ordering for observation n , β is a vector of estimable parameters, and ε is a disturbance term. Using this equation, observed ordinal data, y_n , are defined as (with 1 = extremely unlikely, 2 = unlikely, 3 = unsure, 4 = likely, and 5 = extremely likely)

$$\begin{aligned} y_n &= 1 && \text{if } z_n \leq \mu_0 \\ &= 2 && \text{if } \mu_0 < z_n \leq \mu_1 \\ &= 3 && \text{if } \mu_1 < z_n \leq \mu_2 \\ &= 4 && \text{if } \mu_2 < z_n \leq \mu_3 \\ &= 5 && \text{if } z_n \geq \mu_3, \end{aligned} \quad (2)$$

where μ 's are estimable parameters (referred to as thresholds) that define y_n and are estimated jointly with the model parameters β . The estimation problem then becomes one of determining the probability of the five specific ordered responses for each observation n . This is done by making an assumption on the distribution of ε_n in Equation (1). If ε_n is assumed to be normally distributed across observations an ordered probit model results (alternatively, if ε_n is assumed to logistic distributed an ordered logit model results). Note that without loss of generality μ_0 can

be set equal to zero requiring estimation of three thresholds, μ_1 , μ_2 , and μ_3 .

Assuming the disturbance terms are normally distributed (Washington et al., 2011), the ordered category selection probabilities can be written as (removing subscripting n for notational convenience)

$$\begin{aligned} P(y=1) &= \Phi(-\beta X) \\ P(y=2) &= \Phi(\mu_1 - \beta X) - \Phi(-\beta X) \\ P(y=3) &= \Phi(\mu_2 - \beta X) - \Phi(\mu_1 - \beta X) \\ P(y=4) &= \Phi(\mu_3 - \beta X) - \Phi(\mu_2 - \beta X) \\ P(y=5) &= 1 - \Phi(\mu_{I-1} - \beta X), \end{aligned} \quad (3)$$

where $\Phi(\cdot)$ is the cumulative normal distribution.

For model interpretation, a positive value of β implies that an increase in \mathbf{X} will increase the probability of getting the highest response (extremely likely) and decrease the probability of getting the lowest response (extremely unlikely), but to interpret the intermediate categories (to estimate the direction of the effects of the interior categories of unlikely, unsure and likely) and the probability effect of any variable in the vector \mathbf{X} on each outcome category, average marginal effects are computed at the sample mean as Equation (4) given below (Washington et al., 2011).

$$\frac{P(y=n)}{\partial X} = [\phi(\mu_{n-1} - \beta X) - \phi(\mu_n - \beta X)]\beta, \quad (4)$$

Here, $P(y=n)$ is the probability of outcome n , μ represents the thresholds, and $\phi(\cdot)$ is the probability mass function of the standard normal distribution. The computed marginal effects quantify the effect that a one-unit change of an explanatory variable will have on outcome category n 's selection probability.

Finally, there is likely unobserved heterogeneity present in the data that would result in the effect of explanatory variables to vary across individual observations or groups of observations. To account for this possibility, in the transportation literature, researchers have used random parameters models, latent class (finite mixture) models, Markov switching models, or combinations of these approaches. Using a model structure that can potentially account for unobserved heterogeneity is important because constraining parameters to be fixed across observations when they actually vary across observations can lead to inconsistent, inefficient, and biased parameter estimates (Mannering, Shankar, & Bhat, 2016). In this paper, the possibility of parameters varying across observations is considered by estimating a random parameters formulation with

$$\beta_i = \beta + \varphi_i, \quad (5)$$

where β_i is a vector of observation parameters and φ_i is a randomly distributed term (for example, normally distributed term with mean zero and variance σ^2). Estimation of this random parameters formulation is done by simulated maximum likelihood estimation, and we will use a 500 Halton-draw sequencing approach for the simulation as is commonly done in the literature (Anastasopoulos & Mannering, 2009; Bhat, 2003).

6. Model estimation results

Peoples' willingness to relinquish one of their household's vehicles in the presence of SAVs is likely to be much different in a single-vehicle household than it is in a multivehicle household (households owning two or more vehicles). This is because, among other possible reasons, single-vehicle households may have stronger resistance of relinquishing their only vehicle so as to be exposed to more uncertainty with regard to the effectiveness of SAV as a transportation mode relative to conventional vehicle ownership, especially during hurricane, earthquake, or other natural disasters. To test if separate statistical models should be estimated for single- and multivehicle households, a likelihood ratio test is conducted with the test statistic $X^2 = -2[LL(\beta_{total}) - LL(\beta_{single}) - LL(\beta_{multi})]$, where the $LL(\beta_{total})$ is the log-likelihood at convergence of the model using all respondents (both single- and multi-vehicle households), $LL(\beta_{single})$ is the log-likelihood at convergence using only respondents from single-vehicle households, and $LL(\beta_{multi})$ is the log-likelihood at convergence using only respondents from multivehicle households. This test statistic is χ^2 distributed with degrees of freedom equal to the difference in the number of parameters of both of the models. The value of X^2 is 42.44, and with 21 degrees of freedom. We are more than 99% confident that the null hypothesis that the single- and multivehicle household respondents are the same can be rejected. Thus separate models are estimated for single- and multivehicle households.

A likelihood ratio test was also conducted to determine if there were significant differences between the University of South Florida and American Automobile Association respondents. In both single- and multivehicle household models, we

could not reject the null hypothesis that the two survey groups were the same at reasonable confidence levels. Thus we do not estimate separate models for these two survey groups.

Random parameters ordered probit model results of peoples' willingness to relinquish one of their household vehicles in the presence of SAVs are presented in Table 2 (for respondents from single-vehicle households) and Table 3 (for respondents from multivehicle households). In Table 4, the average marginal effects of the individual variables are presented in order to assess the influence of specific parameters on the probabilities of the five possible outcomes (extremely unlikely, unlikely, unsure, likely, and extremely likely). Parameters producing statistically significant standard deviations for their assumed distribution are treated as parameters that vary across the population (with each observation having its own parameter), and the remaining parameters are treated as fixed parameters because the standard deviations are not significantly different from zero (one parameter for all observations).

Table 2 shows that for respondents from single-vehicle households, seven parameters (indicators for male respondent, post graduate, single licensed driver household, moderate commute distance, high daily travel time, crash, and complete vehicle damage) were found to vary significantly across the population. Table 3 shows that for respondents from multivehicle households, five parameters (indicators for male respondent, moderate commute distance, high daily travel time, crash, and complete vehicle damage) were found to vary significantly across the population. Again, a likelihood ratio test was used to statistically compare the random parameters and fixed parameters ordered probit models for both single- and multivehicle household respondents. The likelihood ratio test statistic is calculated as $X^2 = -2[LL(\beta_{random}) - LL(\beta_{fixed})]$, where the $LL(\beta_{random})$ is the log-likelihood at convergence of the random-parameter ordered probit model and the $LL(\beta_{fixed})$ is the log-likelihood at convergence of the fixed-parameter ordered probit model. The test statistic X^2 is χ^2 distributed with degrees of freedom equal to the difference in the number of parameters of both fixed and random parameters models. For respondents from single-vehicle households, the value of X^2 is 17.97, and with 7 degrees of freedom. We are more than 98% confident that the null hypothesis that the random- and fixed-parameters ordered probit models are equal can be rejected (thus justifying the use of the random parameters formulation). For respondents from multivehicle households, the value of X^2 is 11.97, and with 5 degrees of freedom, we are more than 97% confident that the null hypothesis that the random- and fixed-parameters ordered probit models are equal can be rejected (thus justifying the use of the random parameters formulation).

7. Discussion of estimation findings

As shown in Tables 2 and 3, gender is a statistically significant factor in relinquishing vehicle ownership in the presence of SAVs in both single- and multivehicle households. From the marginal effects in Table 4, being male, on average, increases the probability of being unlikely or extremely unlikely to relinquish a household vehicle in a single-vehicle household, but decreases these probabilities in multivehicle households, relative to their female counterparts in the presence of SAVs

Table 2. Single-vehicle household (households owning only one vehicle) random parameter ordered probit model estimation of respondents' willingness to relinquish a household vehicle with the introduction of shared autonomous vehicles (extremely unlikely, unlikely, unsure, likely, extremely likely). All random parameters are normally distributed.

Variable description	Estimated parameter	t statistic
Constant	1.435	6.50
Male respondent indicator (1 if respondent is male, 0 otherwise) <i>Standard deviation of parameter</i>	-0.211 (1.627)	-1.61 (12.38)
Millennial indicator (1 if respondent is classified as a millennial, 0 otherwise)	0.679	4.54
Post graduate indicator (1 if respondent's highest educational qualification is a post graduate degree, 0 otherwise) <i>Standard deviation of parameter</i>	0.119 (0.821)	0.92 (7.43)
Multiperson household indicator (1 if respondent is a member of a household with more than 3 persons, 0 otherwise)	0.935	4.21
Single licensed driver household indicator (1 if respondent is a member of a household with only one licensed driver, 0 otherwise) <i>Standard deviation of parameter</i>	-0.258 (1.456)	-1.83 (12.06)
Moderate commute distance indicator (1 if respondent travels a one-way distance less than 10 miles for their commute, 0 otherwise) <i>Standard deviation of parameter</i>	0.231 (1.221)	1.70 (9.98)
High daily travel time indicator (1 if respondent travels more than 90 minutes every day for all their trips, 0 otherwise) <i>Standard deviation of parameter</i>	-0.662 (2.150)	-3.44 (9.64)
Low parking time indicator (1 if respondent spends 5 minutes or less in order to park their vehicle, 0 otherwise)	-0.592	-4.36
Crash indicator (1 if respondent has been involved in a traffic crash in the past, 0 otherwise) <i>Standard deviation of parameter</i>	0.101 (1.239)	0.70 (12.60)
Complete vehicle damage indicator (1 if respondent was in a crash that resulted in their vehicles suffering complete damage, totaled, 0 otherwise) <i>Standard deviation of parameter</i>	-0.424 (1.121)	-2.52 (7.32)
Threshold, μ_1	2.168	13.55
Threshold, μ_2	3.406	16.93
Threshold, μ_3	5.308	17.36
Number of observations		417
Log-likelihood at convergence		-581.017
Restricted log-likelihood		-607.209

(however, in both single- and multivehicle households, the model estimations produced a statistically significant random parameter suggesting considerable heterogeneity across the population). Although the probability influences of the male indicator variables are small on average in both models, part of the reason for this statistically significant male/female difference could be due to men being more risk averse with respect

to new vehicle technologies in single-vehicle households and less risk averse in multivehicle households relative to females. In fact, there is a large body of literature showing gender differences in risk taking in transportation-related decisions (Abay & Mannering, 2016).

Comparing across generations, millennials (respondents who are less than 35 years of age) are more likely or extremely

Table 3. Multivehicle household (households owning two or more vehicles) random parameter ordered probit model estimation of respondent's willingness to relinquish a household vehicle with the introduction of shared autonomous vehicles (extremely unlikely, unlikely, unsure, likely, extremely likely). All random parameters are normally distributed.

Variable description	Estimated parameter	t statistic
Constant	1.000	6.45
Male respondent indicator (1 if respondent is male, 0 otherwise) <i>Standard deviation of parameter</i>	0.119 (0.622)	1.49 (11.41)
Millennial indicator (1 if respondent is classified as a millennial, 0 otherwise)	0.593	4.33
White respondent indicator (1 if respondent is classified as white, 0 otherwise)	-0.346	-3.03
Post graduate indicator (1 if respondent's highest educational qualification is a post graduate degree, 0 otherwise)	0.305	3.76
Single licensed driver household indicator (1 if respondent is a member of a household with only one licensed driver, 0 otherwise)	-0.706	-4.47
Vehicle ownership indicator (1 if respondent is a member of a household that owns more than three vehicles, 0 otherwise)	-0.289	-3.54
Moderate commute distance indicator (1 if respondent travels a one-way distance less than 10 miles for their commute, 0 otherwise) <i>Standard deviation of parameter</i>	0.362 (0.386)	3.70 (4.50)
High daily travel time indicator (1 if respondent travels more than 90 minutes every day for all their trips, 0 otherwise) <i>Standard deviation of parameter</i>	0.174 (0.926)	1.54 (8.26)
Low parking time indicator (1 if respondent spends 5 minutes or less in order to park their vehicle, 0 otherwise)	-0.184	-2.18
Crash indicator (1 if respondent has been involved in a traffic crash in the past, 0 otherwise) <i>Standard deviation of parameter</i>	0.272 (0.538)	2.33 (11.26)
Complete vehicle damage indicator (1 if respondent was in a crash that resulted in their vehicles suffering complete damage, totaled, 0 otherwise) <i>Standard deviation of parameter</i>	-0.165 (0.646)	-1.52 (7.45)
No injury severity indicator (1 if the respondent was involved in one or more crashes, but no respondent-involved crashes resulted in injury, 0 otherwise)	-0.210	-2.14
Threshold, μ_1	0.816	15.14
Threshold, μ_2	1.548	22.55
Threshold, μ_3	2.737	28.03
Number of observations		797
Log-likelihood at convergence		-1195.938
Restricted log-likelihood		-1238.243

Table 4. Average marginal effects of the random parameter ordered probit model estimation of respondent's willingness to relinquish a household vehicle with the introduction of shared autonomous vehicles for single-vehicle households (multivehicle household values in parentheses).

Variable description	Average marginal effects				
	Extremely unlikely	Unlikely	Unsure	Likely	Extremely likely
Male respondent indicator (1 if respondent is male, 0 otherwise)	0.037 (−0.034)	0.020 (−0.014)	−0.048 (0.011)	−0.009 (0.029)	−0.00026 (0.008)
Millennial indicator (1 if respondent is classified as a millennial, 0 otherwise)	−0.108 (−0.132)	−0.088 (−0.093)	0.016 (0.016)	0.036 (0.148)	0.00015 (0.061)
White respondent indicator (1 if respondent is classified as white, 0 otherwise)	− (0.086)	− (0.050)	− (−0.019)	− (−0.087)	− (−0.030)
Post graduate indicator (1 if respondent's highest educational qualification is a post graduate degree, 0 otherwise)	−0.020 (−0.082)	−0.013 (−0.039)	0.028 (0.023)	0.005 (0.076)	0.00016 (0.022)
Multiperson household indicator (1 if respondent is a member of a household with more than 3 persons, 0 otherwise)	−0.096 (−)	−0.226 (−)	0.232 (−)	0.090 (−)	0.00078 (−)
Single licensed driver household indicator (1 if respondent is a member of a household with only one licensed driver, 0 otherwise)	0.045 (0.239)	0.030 (0.028)	−0.059 (−0.096)	−0.011 (−0.143)	−0.00033 (−0.028)
Vehicle ownership indicator (1 if respondent is a member of a household that owns three or more vehicles, 0 otherwise)	− (0.082)	− (0.033)	− (−0.027)	− (−0.070)	− (−0.019)
Moderate commute distance indicator (1 if respondent travels a one-way distance less than 10 miles for their commute, 0 otherwise)	−0.038 (−0.092)	−0.031 (−0.051)	0.054 (0.022)	0.011 (0.091)	0.00035 (0.030)
High daily travel time indicator (1 if respondent travels more than 90 minutes every day for all their trips, 0 otherwise)	0.149 (−0.046)	−0.004 (−0.023)	−0.126 (0.013)	−0.019 (0.044)	−0.00044 (0.013)
Low parking time indicator (1 if respondent spends 5 minutes or less in order to park their vehicle, 0 otherwise)	0.106 (0.050)	0.053 (0.023)	−0.132 (−0.015)	−0.026 (−0.046)	−0.00086 (−0.013)
Crash indicator (1 if respondent has been involved in a traffic crash in the past, 0 otherwise)	−0.018 (−0.080)	−0.009 (−0.028)	0.023 (0.028)	0.004 (0.064)	0.00012 (0.016)
Complete vehicle damage indicator (1 if respondent was in a crash that resulted in their vehicles suffering complete damage, totaled, 0 otherwise)	0.085 (0.048)	0.018 (0.018)	−0.089 (−0.016)	−0.014 (−0.040)	−0.00037 (−0.010)
No injury severity indicator (1 if respondent suffered no injuries in their most severe crash, 0 otherwise)	− (0.060)	− (0.024)	− (−0.019)	− (−0.051)	− (−0.014)

likely to relinquish a household vehicle with the introduction of SAVs in both single- and multivehicle households, relative to other age groups (as shown in the marginal effects in Table 4). Millennials are a significant demographic in determining the course of future technology adoption, as they are the largest living generation (Fry, 2016) and are set to dominate the future discussions and discourse on adoption of new technologies. These results are also in line with recent literature that looked at generational-level differences in the adoption of new technology (Anderson, 2015; Smith, 2011; Smith, 2013), and millennials' willingness to use multiple modes of transportation to reach a destination and the differences in their overall travel behavior and preferences toward more equitable modes of transportation (APTA, 2013; Circella et al., 2016). The results also make intuitive sense, considering millennials' attitude toward vehicle ownership and a sharing economy (Circella et al., 2016).

Marginal effects in Table 4 show that white respondents (1 if respondents are classified as white for ethnicity, 0 otherwise) tend to be more unlikely or extremely unlikely to relinquish a household vehicle in multivehicle households relative to other ethnicities (this indicator variable was statistically insignificant in single-vehicle households). Past literature has touched upon the higher levels of accessibility to automobiles enjoyed by whites (Berube, Deakin, & Raphael, 2006) and their general reluctance to engage in shared transportation modes such as carpools (McKenzie, 2015). This seems to be particularly true in multivehicle households.

In contrast, respondents with a graduate degree (1 if respondents whose highest qualification was a graduate degree, 0 otherwise), in both single- and multivehicle households, have

higher probabilities to be likely or extremely likely to relinquish a household vehicle to utilize SAVs when they become available in the market relative to other educational levels (see Table 4). However, in single-vehicle households, the effect of the variable was found to vary significantly across respondents (producing a statistically significant random variable), suggesting considerable heterogeneity across observations, whereas this variable produced a fixed parameter in the case of multivehicle households. In both single- and multivehicle households, it is likely that a higher level of education exposes respondents to greater discourse and discussion on the benefits of AVs and shared economies.

In single-vehicle households with three or more household members, respondents, on average, were found to be less unlikely or extremely unlikely (Table 4) to relinquish a household vehicle (this variable was statistically insignificant in the multivehicle household model) relative to one- and two-person households. This would seem to support the hope that SAVs can substantially improve mobility among larger households that are currently restricted by owning only a single vehicle.

Estimation results in both single- and multivehicle models show that households with a single licensed driver (1 if respondents belong to households with only one licensed driver, 0 otherwise), on average, are more unlikely or extremely unlikely to give up a household vehicle with the availability of SAV alternatives (Table 4). Interestingly, this variable produced a statistically significant random parameter in the single-vehicle case (suggesting considerable heterogeneity across the sample) and a fixed parameter in the multivehicle case. In both cases, it is likely that such households may have transportation patterns that make them less willing to rely on sharing.

For the case of multivehicle households, households owning three or more vehicles were found to be more unlikely or extremely unlikely to relinquish one of their vehicles (see marginal effects in Table 4) relative to their two-vehicle multivehicle household counterparts. It appears as though respondents in households with a large number of vehicles seem to be more entrenched in the private-vehicle ownership culture and, thus, less likely to relinquish in favor of SAVs. Another possible reason is that high-vehicle-ownership respondents may own one or more vehicles largely for enjoyment and collection purposes, which would make their relinquishment less likely. It is noteworthy that other household attributes such as household income were considered in the modeling process, but found to be statistically insignificant.

A number of model results show the impacts of current travel characteristics on vehicle ownership decisions. For example, in both single- and multivehicle households, if a respondent commutes a one-way distance of fewer than 10 miles, on average, they tend to be less unlikely or extremely unlikely to give up a household vehicle (Table 4). The effect of this variable varies across the population in both vehicle-ownership-level models (Tables 2 and 3), again implying heterogeneous effects suggesting, for example, that not all less than 10-mile commutes are the same.

In addition to commute distance, total daily travel time was found to significantly influence vehicle-relinquishment decisions (Table 4), with respondents from single-vehicle households who traveled more than 90 minutes on all travel in a day being more extremely unlikely to relinquish a household vehicle, and respondents from multivehicle households who traveled more than 90 minutes on all travel in a day being less unlikely and extremely unlikely to relinquish a household vehicle (Table 4). Although the effect of this variable was found to vary significantly across the respondent population in both models (as reflected by the presence of a statistically significant random parameter), the findings suggest the substantive differences in the way single- and multivehicle households view travel times and vehicle ownership needs.

With regard to the possible effects of parking on SAV adoption, for both single- and multivehicle household respondents, those respondents who spent 5 minutes or less on an average to park their vehicles during their commute trips were more unlikely or extremely unlikely (Table 3) to relinquish a household vehicle relative to people that spend longer periods parking. This shows, as expected, that parking scarcity is likely to be a major driver in SAV adoption.

Three variables relating to crash history were found to be statistically significant in the model; an indicator depicting respondents' involvement in a crash, an indicator for respondents that experienced complete vehicle damage in a crash, and an indicator for respondents that did not sustain an injury in their most severe crash. In both single- and multivehicle households, respondents who have been involved in a crash are, on average, more likely or extremely likely to relinquish a household vehicle with the introduction of SAVs (Table 4), although the effects of this variable are heterogeneous across the population as indicated by the significant random parameter.

Among those who were involved in one or more traffic crashes, in both single- and multivehicle households,

respondents who suffered complete vehicle damages in one of their crashes are, on average, more unlikely or extremely unlikely to relinquish a household vehicle than those who experienced moderately severe crashes, although again the effect of this variable varies across observations. It is likely that these respondents, who have experienced extensive-damage crashes, are more skeptical of emerging vehicle technologies, such as AVs, because of safety-related concerns. At the other extreme of crash severity, respondents in multivehicle households, who were in one or more crashes but did not sustain injuries in any crash, were also found to be more unlikely or extremely unlikely to relinquish a household vehicle. Since these people have had crash experiences with favorable injury outcomes, they may discount the potential safety benefits of SAVs and thus may be more reluctant to relinquish one of their vehicles than those who experienced moderately severe crashes.

Finally, it is noteworthy that variables such as household income and others were not found to be statistically significant in the models. It appears that the variables we have included (while obviously correlated with many variables not found to be significant) are statistically the best in terms of modeling people's vehicle relinquishment likelihoods in the presence of SAVs.

8. Summary and conclusions

This paper presents an initial assessment of people's likelihood of relinquishing a household vehicle (reducing their household vehicle ownership level by one) in the presence of SAVs. To this end, we conducted a survey of two different target groups of interest: faculty, students, and staff from a large university (University of South Florida); and the members of the AAA Foundation of the southeastern United States, asking how likely they are to consider relinquishing one of their household's personal vehicles if SAVs were available (thus reducing their household vehicle ownership level by one). Possible responses to the question are: extremely unlikely, unlikely, unsure, likely, and extremely likely. For single-vehicle households, this would be relinquishing their only vehicle, and for multivehicle households (households owning two or more vehicles) this would be relinquishing one of their vehicles. Therefore, two different random parameters ordered probit models are estimated to analyze the factors that influence the households' likelihood of relinquishing one of their vehicles: one model for single-vehicle households and the other model for multivehicle households.

Our estimation results show that for single-vehicle households, seven parameters (indicators for male respondent, post graduate, single licensed driver household, moderate commute distance, high daily travel time, crash, and complete vehicle damage) were found to vary significantly across the population and for multivehicle households, five parameters (indicators for male respondent, moderate commute distance, high daily travel time, crash, and complete vehicle damage) were found to vary significantly across the population. Different influential factors relating to gender, respondent characteristics, household characteristics, current travel characteristics, and crash history are statistically significant and affect the likelihood of vehicle relinquishment with the introduction of SAVs. The findings from

this study provide key insights regarding vehicle relinquishment in an era of SAVs, including the following:

1. Gender has a significant but variable impact on people's likelihood of relinquishing a household vehicle when SAVs become available in the market. Males, on average, had lower probabilities of being likely or extremely likely to relinquish a household vehicle in single-vehicle household, but had higher probabilities in these categories in multivehicle households, relative to their female counterparts.
2. Socioeconomic characteristics are significant indicators toward people's likelihood of relinquishing a household vehicle for SAVs. For instance, millennials and graduate degree holders are more likely to relinquish a household vehicle when SAVs come into the market, possibly indicating their preferences toward a more sustainable lifestyle in comparison to their older counterparts.
3. Respondent commute distances and average daily travel times have a complex effect on the likelihood of relinquishing vehicles, one that varies considerably between single- and multivehicle households.
4. While previous crash history usually makes respondents more likely to relinquish their vehicles to use emerging technologies like SAVs, a previous experience of suffering complete vehicle damage or no injury makes people more unlikely to relinquish their vehicles in order to use SAVs (than those who experienced moderately severe damages).
5. Throughout our model estimations, there are substantial and statistically significant differences between single- and multivehicle household respondent opinions. This underscores the potentially large impact that the traditional human-driven-vehicle culture may have on new technology adoptions.

The insights obtained from this study can be used to target demographic groups most likely to adopt SAVs. The study can also help better understand the sentiments of the public relating to their willingness to use such emerging technologies. However, it is important to keep in mind that people's perception of SAVs is not likely to be temporally stable. As AV technologies unfold, personal experiences, publicity, and information gathering will undoubtedly change people's perceptions of SAVs. Thus, it is important to view the findings in this paper with some caution in light of this. Future studies could examine the sentiments of the general public towards AVs and utilizing SAVS when they become available in the market. Yet, the marginal effects and the initial findings from this paper will serve as a baseline for comparison of changes in people's intentions as additional studies are conducted in the future.

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