MODELING AMERICANS' AUTONOMOUS VEHICLE PREFERENCES: A FOCUS ON DYNAMIC RIDE-SHARING, PRIVACY & LONG-DISTANCE MODE CHOICES

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ABSTRACT

Rapid advances in technologies have accelerated the timeline for public use of fully-automated and communications-connected vehicles. Public opinion on self-driving vehicles or AVs is evolving rapidly, and many behavioral questions have not yet been addressed. This study emphasizes AV mode choices, including Americans' willingness to pay (WTP) to ride with a stranger in a shared AV fleet vehicle on various trip types and the long-distance travel impacts of AVs. Exactly 2,588 complete responses to a stated-preference survey with 70 questions provide valuable insights on privacy concerns, safety and dynamic ride-sharing with strangers, long-distance travel and preferences for smarter vehicles and transport systems. Two hurdle models (which allow for a high share of zero-value responses) were estimated: one to predict WTP to share a ride and another to determine WTP to anonymize location while using AVs, and a multinomial logit was developed to estimate long-distance mode choices with AVs and SAVs available. Results suggest that WTP to share rides will rise over particularly popular for long-distance business travel. Elasticity estimates suggest that privacy may not be an important concern for AV-based travel.

Keywords: Autonomous vehicles, shared, dynamic ride-sharing, travel behavior survey, willingness to pay, mode choice, privacy.

MOTIVATION

Roughly 30 U.S. states have already passed legislation relating to fully automated, or autonomous, vehicles (AVs) and a federal law is underway (Stocker and Shaheen, 2019). Several companies, like Waymo, Lyft, and Ford Motor Company are testing AVs on public roads. With increasing access to these vehicles, the public opinions regarding vehicle automation and AVs are evolving rapidly. Past studies suggest that AVs are becoming more acceptable over time and may be a real mode option for use in the relatively near future (see, e.g., Vujanic and Unkefer, 2011; Schoettle and Sivak, 2014; Bansal and Kockelman, 2018). Sommer (2013) reported that around half of Americans were concerned about riding in an AV, even though they admitted to the technology's many benefits, and this view was supported by respondents' answers in Schoettle and Sivak's (2014) survey. Another U.S. survey, by Kelly Blue Book (2016), suggests that respondents believed conventional vehicles are still safer than AVs – at least for the time-being. Schoettle and Sivak's (2016) second AV survey revealed similar reactions, with more than 35% of U.S. respondents very concerned about AVs, and partial autonomy less feared. Deloitte (2014), MIT AgeLab (Abraham *et al.,* 2016), Bansal and Kockelman (2018), Lee et al. (2017), Krueger et al. (2016), Haboucha et al. (2017), and Lavieri et al. (2017) have all concluded from their surveys that younger people are more likely to use AVs. Demographic evolution encompassing entire nations (like population aging) is also important to consider, when anticipating the future use and adoption of advanced transport technologies. Until AVs are widely available in showrooms, at reasonably affordable prices, there will be regular fluctuations in public perceptions in any country or setting. Thus, regular survey efforts, and better surveys, with greater nuance, can make valuable contributions to transportation planning, policymaking, and vehicle production decisions.

Ride-sourcing is a pre-arranged or on-demand form of mobility arranged via smartphone applications (Stocker and Shaheen, 2017). Ride-sourcing demand and supply have risen over time, especially in dense settings like San Francisco (SFMTA, 2015). Real-time or dynamic ride-sharing (DRS) is becoming popular as a new form of carpooling. DRS is offered by ride-sourcing companies (via, for example, uberPool and Lyft Line), and travelers share rides with strangers in order to lower costs. Many recent studies illuminate the operational benefits of DRS (see, e.g., Agatz *et al.*, 2010; Bischoff *et al.,* 2016; Fagnant and Kockelman, 2018; Loeb *et al*., 2018; Farhan and Chen, 2018; Gurumurthy and Kockelman, 2018; Gurumurthy et al., 2019). Since AVs will be expensive to acquire for personal use (Fagnant and Kockelman, 2015), a shift towards shared AVs (SAVs) and DRS is likely.

Greenblatt and Shaheen (2015) conducted a study on AVs and their synergy with on-demand mobility, such as ride-sourcing and DRS, and concluded that many energy and emission benefits arise from fusing the services, but provide no quantifiable result on user's willingness to share rides (with strangers) to acquire those benefits. Bansal and Kockelman (2018) estimated SAV use for different pricing levels, with respondents unwilling to use SAVs at the time, but did not consider DRS. Quarles and Kockelman (2018) estimated that 16% of Americans are willing to share rides with strangers by paying about 40 percent less (e.g., 60 ¢/mile rather than $1 per mile of SAV use). However, travelers' reactions to different vehicle response times and wait times has not been carefully investigated. Detailed DRS investigations are few. A recent Swiss stated-preference survey by Stoiber et al. (2019) reveals that SAVs with DRS are likely to be more popular than privately-owned AVs. Comfort, cost and travel time characteristics of SAVs with DRS are expected to help increase use. Krueger *et al.* (2016) captured certain nuances by modeling a discrete choice decision between SAVs without DRS, SAVs with DRS and a respondent-specific travel alternative. They concluded that DRS is a preferred option among young people and people who regularly use carsharing services, and service parameters (like response times) can impact these preferences. Lavieri and Bhat (2019) corroborated this finding using data from the Dallas-Fort Worth area, with their results showing travel delays impacting the share-ride decision much more than the notion that one is traveling with a stranger. They note the importance of trip type on willingness to share rides, with commute trips more likely to be shared and an average 50¢/mi willingness to pay to avoid sharing.

Americans are increasingly concerned about the use of personal information. Smartphone GPS can record the user's locations, and internet-related services curate advertisements specific to each user. Such concerns may be exacerbated with AV cameras and cell connectivity (Schoettle and Sivak, 2014). For example, SAVs may rely on facial recognition to confirm pickup and dropoff.

Existing work on related public opinions remains weak: e.g., what are people willing to pay for privacy-enforcing measures? This survey paper tackles such questions.

Related to this, automation can pose ethical dilemmas. Bonnefon *et al.* (2016) and Goodall (2017) believe that public opinion must be considered in crash-response programming and the like. Jenkins (2016) and Lin (2017) described several possible outcomes of an inevitable crash scenario, and Fleetwood (2017) censured algorithms that teach AVs to choose targets by force, arguing that they should not be readily allowed for public use. However, the public perception of what is most ethical in crash response contexts, and other situations, like who is to blame for a computer's decision or criteria to pass to be allowed to use SAVs, is yet to be determined. This paper's survey adds new questions and public opinions to that discussion.

Finally, the long-distance (LD) travel implications of AVs are an important consideration. LaMondia *et al.* (2016) introduced AVs as new mode for LD trips originating in Michigan to understand changing mode shares and found a decline in air travel as a possibility, with mode share being lost to AVs. Bansal and Kockelman (2017, 2018) suggested that LD-trip frequency may well double, and Perrine *et al*. (2019) predict major losses (on the other of 50%) in U.S. airline revenues (for domestic trips), long term, once AVs are widely available. Huang et al. (2019) used a traditional travel demand model with destination and mode choices in order to anticipate shifts in travel patterns from conventional modes to SAVs and autonomous trucks. While these studies probe into system aggregate impact for LD trips, modeling effort to capture primary influential factors in LD trip making are not entirely captured. Questions probing actual Americans on these topics and factors that are tied into developing trends can then be modeled to better understand LD travel. Table 1 provides some key takeaways from the research described including critical gaps in literature.

Table 1: Evolution of Stated User Preferences on Shared Autonomous Vehicle Use

<table>
<tr><th>Past Research</th><th>Key Takeaways</th></tr>
<tr><td>Deloitte (2014)</td><td rowspan="8">AV and SAV users will likely be young travelers with college degrees, and those traveling for longer distances. Travelers may be willing to use SAVs when offered at around $1 per mile.</td></tr>
<tr><td>Abraham et al. (2016)</td></tr>
<tr><td>Schoettle and Sivak (2014)</td></tr>
<tr><td>Schoettle and Sivak (2016)</td></tr>
<tr><td>Lavieri et al. (2017)</td></tr>
<tr><td>Lee et al. (2017)</td></tr>
<tr><td>Haboucha et al. (2017)</td></tr>
<tr><td>Bansal and Kockelman (2018)</td></tr>
<tr><td>Bonnefon et al. (2016)</td><td rowspan="2">AV-related privacy concerns on sharing location, facial, and travel-pattern data exist. User apprehension and willingness-to-pay to protect privacy when using sensor-loaded AVs need to be investigated and quantified.</td></tr>
<tr><td>Fleetwood (2017)</td></tr>
<tr><td>Krueger et al. (2016)</td><td rowspan="4">User willingness to share rides is expected to vary by trip type and depend on added travel times. Discounted fares for sharing rides encourages DRS, but the elasticities of such behaviors are unknown.</td></tr>
<tr><td>Quarles and Kockelman (2018)</td></tr>
<tr><td>Stoiber et al. (2019)</td></tr>
<tr><td>Lavieri and Bhat (2019)</td></tr>
</table>

This paper addresses many such investigative gaps. A description of the survey design and data processing methods are presented next, followed by summary statistics, model formulation, results discussion, and various conclusions.

SURVEY DESIGN & DATA PROCESSING

The survey consists of 70 questions, tackling various aspects of AV and SAV use, including DRS preferences (which are rides shared with strangers), privacy and security concerns, ethical implications of crash response algorithms, long-distance travel shifts, and future travel choices, with each subject section having about 5 to 8 questions. This paper focuses on responses to DRS, privacy, crash ethics and long-distance questions.[1]

AVs and SAVs are introduced to respondents of the survey before they were shown the questions. A futuristic setting is described with AVs and SAVs being fully-automated, which is also referred to as SAE Level 5 driving automation[2]. Personal AVs are hypothesized to be relatively unaffordable while private SAV rides are described to be widely available in the next 10 years and reasonably affordable at $1.50/mi. This was then followed up with a section on current AV perceptions including questions on impressions of and WTP for AVs, SAV use, and DRS with strangers. Questions regarding an acceptable age for children/young people to travel individually or in a group were also asked, along with questions regarding opportunities for serving persons with disabilities. A slider response was used to obtain continuous responses on WTP, including for DRS with a stranger - by time of day (night vs. daytime) and assuming different time delays. An open-ended slider response can lead to response biases, but Miller et al. (2011) have shown that this approach still leads to appropriate policy decisions. The value of providing one's location en route (to a close friend or family member, to increase travelers' sense of security) was also addressed, when sharing an SAV ride with an unknown person. To assess the ethical implications, three distinct ethical dilemmas were posed to the respondents: two regarding AV crashes with a pedestrian and other cars on the road, and one addressing crash responsibility. Questions on LD travel were based on mode-choice preferences for different types of trips in the presence of affordable AVs and SAVs, following the traditional choice experiment. A demographic section was included towards the survey's end, to provide control variables and correct for various sampling biases, to better represent the U.S. population.

Data Collection

Survey Sampling International's (SSI) panel of Americans was used to access respondents from across the United States using Qualtrics, an online survey tool, in June 2017. Biases that are present in personal interviews (Breidert et. al., 2006) are eliminated this way, and incentives along with

[1] Gurumurthy (2017) contains information on results of all questions asked in this extensive survey.
[2] https://www.sae.org/standards/content/j3016_201806/

mandating responses ensured no missing data. Nearly 10,000 Americans were targeted before the required sample attributes were obtained, due to two screening procedures. The first screen blocked respondents from accessing the survey in its entirety if they failed to answer two initial basic questions regarding AVs and SAVs, after relevant information was provided. The second level of screening was done by removing respondents who took less than 15 minutes to complete the survey. This cutoff was estimated from the observed mean response time of 20 minutes from the data, as well as accounting for fast computer/cellphone users who may have taken the survey. Both screens helped ensure respondents were intellectually engaged, and paying attention.

Most questions contained a text input option as "Other: _____" for respondents to elaborate, and expand response options. These inputs were manually mapped to an existing option or to a new option, as appropriate. After screening respondents and remapping responses, usable sample size was n = 2,588 respondents, from across the United States, with purposeful oversampling (n = 1258) of Texans, due to the research sponsor's (the Texas Department of Transportation's) strong interest in understanding Texans' preferences. Both sets of responses are summarized below, after a discussion on sample weighting or expansion.

Population Weighting

The 2,588 complete responses were associated with respondent weights to ensure that all reported statistics and regression analyses reflect the broader population of interest. The U.S. Census Bureau's Public Use Microdata Sample (PUMS) for years 2011-2015 provided national and state percentages across various classifications: location (Texas vs. U.S.), income and race, household size and worker count, vehicle ownership, age, gender, educational attainment and marital status. Certain demographics were under-represented (e.g., males who had not finished high school) and some others were overrepresented (e.g., gender ratio was 47/53 rather than 49/51, 24% of the sample were people 65 years or older rather than 18%), resulting in slightly higher weights. MATLAB code performed iterative proportional fitting over all the combinations of dimensions, ending once categorical percentages fell within 0.001% of the population percentages. Population-weighted sample characteristics are shown in Table 2. All of the following results reflect these adjustments to raw sample statistics.

Table 2: Survey Data's Population-Weighted Summary Statistics

Sample Demographics	Mean	SD	Min	Max
Age (in yrs)	46.00	16.34	21	70
Gender (Male)	48.64 %	-	0	1
Employed Full-Time	37.59 %	-	0	1
Education – Bachelor's	17.56 %	-	0	1
U.S. License Holder	89.77 %	24.86 %	0	1
Disabled	7.91 %	-	0	1
HH Size	2.330	1.047	1	11
HH Annual Income	$70,340	$47,226	$5,000	$250,000
No. of Workers in HH	1.150	0.951	0	5
No. of Children in HH	0.535	0.917	0	9
No. of Vehicles in HH	1.750	0.960	0	6

SUMMARY STATISTICS

Dynamic Ride-Sharing with Strangers and Willingness to Pay (WTP)

Public opinion on dynamic ride-sharing with strangers (while using an SAV) was assessed in detail in this survey. First, a hypothetical 5-mile SAV trip was presented with rising travel times (to reflect delay from adding another passenger) to assess respondents' willingness to share and WTP during the day, while a similar question helped assess WTP in the night. Maximum travel delays that were acceptable by the respondents to share their trips during the middle of the day and during the night were identified. Any added willingness to use DRS when their location was continuously available/broadcast to a family member (or friend) was also recorded, for both cases of day and nighttime trip-making. In addition to these preferences, the ideal cost of using an SAV in order to willingly let go of a currently owned household vehicle was obtained for different SAV response times (i.e., the time taken between a trip request and the SAV's arrival at the traveler's origin). All these results are summarized in Table 4.

As shown in Table 3, only 62.5% Americans and just 54.9% of Texans may be willing to share their ride with strangers when no delay accrues (i.e., no time is added to their 5-mile trip). This willing-to-share-rides pool of respondents reported an average WTP of 74¢ per trip-mile. Interestingly, all scenarios of added travel time returned a similar average. Average WTP by male respondents were compared to female respondents to understand how the perception differed between the two segments. Women seem to retain similar WTP levels of 74¢ even if a 5 min delay accrues, as compared to men having a lower average of 71¢. This may be linked directly to their expectation of security from paying more for the service. However, a t-test for the two means did not prove to be statistically significant at the 95% confidence level. This is also verified in the next section when the data is modeled. Americans (and Texans) may be more interested in their trip distance than their travel time, once they have opted to share their ride. This is analyzed in detail in the next section dealing with model estimation.

TABLE 3: Dynamic Ride-Sharing Preferences during Middle of the Day

Response Variable	U.S.	Texas
Willingness to use SAV with strangers, no additional time		
Yes	22.5%	30.0%
Maybe	40.0%	24.9%
No	37.5%	35.1%
Average WTP (per mile)	$0.74	$0.71

Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
Willingness to use SAV with strangers, 5 min. additional time			*Willingness to use SAV with strangers, 15min. additional time*		
Yes	18.5%	23.2%	Yes	6.0%	8.8%
Maybe	34.8%	31.9%	Maybe	19.1%	21.6%
No	46.7%	45.0%	No	75.0%	69.6%
Average WTP (per mile)	$0.73	$0.69	Average WTP (per mile)	$0.79	$0.65
Willingness to use SAV with strangers, 30 min. additional time			*Willingness to use SAV with strangers, 1 hr. additional time*		
Yes	2.8%	2.7%	Yes	2.2%	2.2%
Maybe	7.9%	15.6%	Maybe	4.2%	5.7%
No	89.4%	81.7%	No	93.6%	92.1%

Average WTP (per mile)	$0.77	$0.65	Average WTP (per mile)	$0.74	$0.62

Table 4 describes willingness to share rides (including trip durations, in DRS mode) during the day and the night. Very few Americans (just 4.4%, vs. 11.0% of Texans) seem willing to share their rides at night (though this may well change, as people become more accustomed to SAV and DRS services in the future). Of those willing to use DRS during the middle of the day, 4.0% more Americans are willing if the service is offered only to people without a prior criminal record. Americans are willing to pay a 10¢-per–mile premium, on average, to share a ride during the night (presumably because they need more chauffeured trips at night [for consumption of alcohol, for example] or expect lower supply of SAVs at night). On average, respondents are more willing to tolerate trip delays at night, presumably because time constraints (on work and school arrivals, for example) are more severe during the daytime.

TABLE 4: Dynamic Ride-Sharing Preferences at Night

Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
Willing to share a ride with a stranger in an SAV during the night?					
Yes				4.4%	11.0%
Maybe, if the stranger has no criminal record				8.0%	5.7%
Maybe, if the stranger's identifying information is given ahead of time				4.0%	5.0%
No				83.7%	78.3%
Average WTP for those willing to share (in $/mile)				$0.87	$0.85
Maximum trip duration for DRS (with a stranger) in an SAV during middle of day (in minutes)					
Mean	29.0	32.6	Median	25.0	26.0
Maximum trip duration for a shared ride in an SAV (with a stranger) during the night (in minutes)					
Mean	34.8	35.4	Median	29.0	30.0
Maximum trip duration between day and night among those willing to share a ride (with a stranger) both in the day and in the night					
Average during the day (in minutes)	40.4	47.5	Average during the night (in minutes)	34.8	35.4

Additional DRS features, like location information broadcast to family or friends for safety purposes, resulted in more people (roughly 15%) willing to share rides (during the day and at night). However, as seen in Table 5, more than 60% of Americans were unwilling to ride-share in an SAV when hinted about additional costs for services while using an SAV. And over 90% seemed hesitant about paying for such a service. Among those willing to pay for such a service, Texans appear to be more concerned about their safety than other Americans.

TABLE 5: Effects of Dynamic Ride-sharing with Trip Location being Broadcasted

Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
Willingness to use SAV to share rides (with a stranger) when location is continuously broadcast to family member or friend					

During the middle of the day…			*During the night…*		
Yes, if the location is constantly broadcasted to family	43.0%	50.1%	Yes, if the location is constantly broadcasted to family	21.8%	30.9%
Yes, even without the location being broadcasted to family	16.4%	18.7%	Yes, even without the location being broadcasted to family	10.4%	7.4%
Not willing to share a ride with anyone	40.6%	31.2%	Not willing to share a ride with anyone	67.8%	61.7%
WTP for location to be broadcasted to family or friends (to enhance trip safety)					
During the middle of the day…			*During the night…*		
Yes	8.6%	7.9%	Yes	6.8%	14.3%
Maybe	18.1%	30.2%	Maybe	8.5%	8.0%
No	73.2%	61.8%	No	84.7%	77.7%
WTP to share a ride with unknown person during the night if trip locations are continuously broadcast to family or friends					
Average WTP (in $/mile)				$0.19	$0.23

Table 6 summarizes the cost that an SAV must be operated at, for different response times, so that the respondent is comfortable letting go of an existing household vehicle. The American Automobile Association (AAA, 2016) estimates that current vehicle ownership and operating costs average 50 to 80 cents per mile, once depreciation of purchase costs is reflected. Those costs can be higher or lower for vehicles driven fewer or more miles per year than the typical U.S. household vehicle. Interestingly, respondents are willing, on average, to pay about that same amount for SAV access – and Texans tend to offer more money than the average American. SAV users can avoid vehicle maintenance and parking costs and hassles, but they cannot guarantee how quickly SAVs will get to them, like they can when walking to their parked vehicle. Actual SAV system experiences will end up impacting everyone's WTP, and service times may vary a fair bit by location (e.g., urban vs. suburban trip ends). It is an interesting evolution of supply and demand that should one day play out around the world.

TABLE 6: Cost of SAVs at Different Response Times to Persuade Reduction in Current Vehicle Ownership

Response Variable	**U.S.**	**Texas**	**Response Variable**	**U.S.**	**Texas**
Cost of using SAV in order to replace vehicles that a respondent's household currently owns (in $/mile)					
Average response time under 1 minute	$0.75	$0.83	Average response time under 10 minutes	$0.52	$0.62
Average response time under 2 minutes	$0.71	$0.75	Average response time under 30 minutes	$0.38	$0.54
Average response time under 5 minutes	$0.64	$0.71			

Privacy Concerns using AVs and SAVs

Privacy is not on top of respondents' minds when general AV-related concerns are requested. However, when targeted as a separate topic, more privacy-related concern was observed. Table 7 demonstrates this, with 89% of Americans (and 83% of Texans) to at least some privacy concerns. However, many respondents (39.8% of Americans and 40.6% of Texans) appear unwilling to pay to anonymize their location while using SAVs. Respondents were also asked to rate their levels of comfort when their location data is used for different socially meaningful purposes. Nearly 48% Americans, on average, were comfortable or somewhat comfortable with this data being used for policing activities, managing traffic and for general community surveillance. However, more than half were against targeted advertising use. Their WTP is modeled in detail in the next section.

TABLE 7: Privacy Concerns Related to AVs and SAVs and WTP for Privacy

Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
WTP for anonymizing user location for the entire trip while using an AV or SAV if they opt in					
Average (in $/trip)				1.10	1.19
Comfort level in allowing trip-location data usage…					
…to aid policing activities with a warrant			*…for general community surveillance*		
Very uncomfortable	17.7%	15.9%	Very uncomfortable	19.2%	26.1%
Somewhat uncomfortable	6.2%	9.1%	Somewhat uncomfortable	14.0%	15.1%
Unsure	22.4%	29.7%	Unsure	30.0%	26.3%
Somewhat comfortable	27.8%	23.6%	Somewhat comfortable	23.8%	21.6%
Very comfortable	25.9%	21.7%	Very comfortable	13.0%	10.9%
…to manage traffic & forecast travel conditions			*…to facilitate directed advertising*		
Very uncomfortable	15.4%	18.8%	Very uncomfortable	42.5%	49.2%
Somewhat uncomfortable	8.7%	12.6%	Somewhat uncomfortable	17.9%	21.3%
Unsure	22.4%	24.3%	Unsure	24.0%	15.9%
Somewhat comfortable	39.0%	30.2%	Somewhat comfortable	11.8%	10.2%
Very comfortable	14.5%	14.1%	Very comfortable	3.8%	3.4%

Crash Ethics While Using AVs

Two distinct crash scenarios were presented in the survey, describing an AV crashing into a group of pedestrians in one case and crashing into other cars on the road in another. Respondents picked from a broad list of options to describe ethical and non-ethical crash outcomes, along with who should be held accountable for such events.

The most popular belief is that AVs should not change course, once a crash is inevitable, and should crash into the first pedestrian or vehicle that crosses its path. Many others feel strongly that vehicle and pedestrian differences should be ignored while heading into a crash. Presumably, Americans recognize that there is no great solution to most crash situations and no new target (like a heavier vehicle or older adult) should be picked, leaving outcomes more to random chance and relatively similar to what humans may do under such difficult situations, with little response time available. Nevertheless, a strong share of respondents (about 20 percent) would like children to be avoided, when feasible, and more crash-worthy vehicles be selected, to minimize loss of life. More than 60% believe that AV manufacturers should be held responsible for such crashes.

MODEL ESTIMATION

Willingness to Pay for Dynamic Ride-Sharing

WTP for DRS in an SAV was estimated in two parts, to reflect the high number of respondents unwilling to share rides with strangers, as shown in Table 8.

Table 8: Respondents Unwilling to Share Rides (in an SAV, for Different Added Times)

Added Time	% Respondents not WTP to Share Rides
0 minutes	37.47%
5	46.70
15	74.99
30	89.37
60	93.63

The two-part model is motivated by Cragg's (1971) hurdle regression specification and was estimated using Stata (StataCorp., 2015). This approach assesses the hurdle beyond which a particular event occurs. Here, the hurdle is one being willing to pay to share a ride and is estimated as a selection variable, s_i, using the maximum likelihood techniques while allowing for unobserved heteroscedasticity (across respondents) as a function of age. Correlation between responses from the same respondent was accounted for using data stratification in Stata, and an independent and identically distributed epsilon is assumed between respondents. A zero-dollar lower bound for each respondent's WTP was imposed as shown below., where $\mathbf{x_i}$ is the vector input of predictor variables affecting this \$0 selection, $\boldsymbol{\beta_1}$ is the associated vector of model coefficients and $\varepsilon_{i,1}$ is (assumed to be) a normally-distributed error term.

$$s_i = \begin{cases} 1 & if\ \mathbf{x}_i\boldsymbol{\beta_1} + \varepsilon_{i,1} > 0 \\ 0 & otherwise \end{cases}$$

Preliminary analysis was conducted to decide between a linear versus an exponential model for the second part of the hurdle model. An exponential model provided a better fit in estimating the two-part model where $s_i = 1$, and also made intuitive sense (as discussed later) and was chosen for this analysis. Both equations are estimated simultaneously using maximum likelihood estimation (MLE). An exponential regression function ensures that WTP estimates can only be positive, with $\mathbf{z_i}$ serving as the vector of predictors or explanatory variables, $\boldsymbol{\beta_2}$ the vector of parameters to be estimated, and $\varepsilon_{i,2}$ as another set of independent, identically distributed normal error terms.

$$\mathrm{Y_i} = \exp(\mathbf{z_i}\boldsymbol{\beta_2} + \varepsilon_{i,2})$$

Table 9 shows the estimated parameters for both the selection model and exponential regression model. As expected, the travel time added via DRS significantly affects respondents' decision to ride-share. Presence of a worker in the household reduces one's willingness, perhaps because workers have more constrained activity patterns, and so desire or need more independent travel. Interestingly, older people (everything else constant) and those with drivers' licenses are estimated to be less likely to share a ride. Those in households with annual incomes between \$75,000 and \$125,000 appear more likely to share a ride, as compared to other income brackets. It is possible that lower income brackets cannot simply afford to use an SAV, while those in higher income brackets prefer private rides.

Respondents with an associate's degree or higher are more willing to share rides (i.e., offer a non-zero valuation for such travel), everything else constant. Interestingly, those currently living in more densely populated but less densely employed neighborhoods appear less willy to share rides, and this could be people living close to downtown where walking gets you to most places.

While coefficients of the exponential regression model cannot be used directly to infer changes in one's expected WTP (due to the non-linear transformation that ensures non-negativity in this response variable), one finds that added travel time does not significantly affect WTP once a traveler is ready to share a ride. Older persons and those without any college education appear to be willing to pay a lower value, assuming they are already willing to share a ride, in this hurdle model specification.

Table 9: Model Estimation Results for WTP to Share a Ride

Selection Model		
Independent Variables	***Coefficients***	***T-stat***
Constant	1.14	4.86
Time added to the shared ride (in minutes)	-0.04	-13.80
Worker present in the household?	-0.30	-2.61
Age of respondent (in years)	-0.01	-3.83
Have U.S. driver's license?	-0.47	-2.59
Household income between $75k and $125k?	0.36	3.22
Has attended some college?	0.26	2.14
Population density (per square mile)	-0.3E-4	-2.99
Employment density (per square mile)	0.5E-4	3.08
Exponential Regression Model		
Independent Variables	***Coefficients***	***T-stat***
Constant	-0.68	-4.82
Age of respondent (in years)	0.01	3.13
Has attended some college?	-0.21	-2.66
Functional Variables for Heteroscedasticity		
Age of respondent (in years): Exponential model	-0.01	-8.00
Fit statistics		
Final log-likelihood		-1992.5321
Pseudo R-square		0.7034
Likelihood Ratio Chi-Square		9450.88
Number of observations (number of respondents)		12,940 (2,588)
F-test (2, 2586)		7.29

The change in response when each of the covariates was changed by one standard deviation was computed to understand how the expected WTP to share rides may change and this is illustrated in Figure 1. For continuous variables, like respondent's age, the marginal expected value of WTP is calculated one standard deviation away from the mean age, in both directions. For indicator variables, the change in responses are determined by completely switching from a base level (like 0), to the next or subsequent levels (for example, 1, 2, or 3) and then calculating the marginal expected value of WTP at that point. Essentially, a continuous covariate's mean, plus/minus one standard deviation, is used to compute the new mean WTP for the sample and this percent change with respect to the previous mean is tabulated, and for indicator variables, these percent change values are calculated by assuming all responses are at a high (that is, 1) or some intermediate point (like 2, 3 or 4 in a multi-level indicator) and then calculating the new mean. Computed changes in expected value of WTP with respect to the initial mean suggests that the lack of a driver's license affects mean values the most, by increasing it by 38%. When everything else is constant, a one standard deviation increase in average age of Americans can reduce the expected WTP by 27%. This means that as Americans continue to age the increase in average age may bring down any WTP to ride-share. As more people fall into the middle-class household income category, results suggest that there will be a 26% increase in average WTP to share rides. People in the suburbs may share rides to cut costs, with a 10% increase for one standard deviation decrease in population density, whereas, high-density employment zones (like the CBD) may see more trips being shared. The elasticity on workers present in the household is remarkably different compared to the covariate in the model developed, showing an increase in WTP when all households have workers and everything else is kept constant.

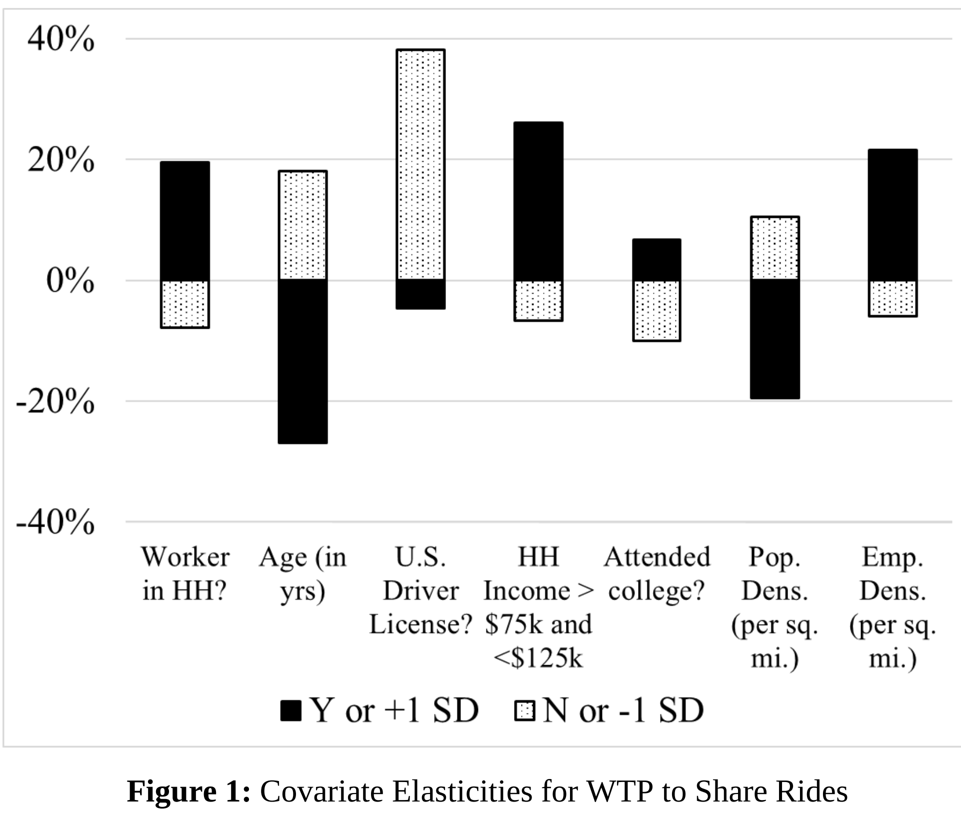

Figure 1: Covariate Elasticities for WTP to Share Rides

Willingness to Pay to Anonymize Location While Using SAVs

A similar hurdle exponential regression was estimated to determine one's WTP to anonymize pick-up and drop-off locations while using SAVs. Table 10 shows the estimated coefficients for the two-part model. As expected, respondents who are concerned about privacy are more likely to be willing to pay to anonymize their location. Disabled people and females are more likely to be willing to pay, perhaps because they feel that they are relatively vulnerable and make an easier target for criminal behaviors. Vehicle ownership is also estimated to increase a respondent's WTP to a non-zero value for this anonymization benefit. Older people and those in smaller households are estimated to be less likely to pay to anonymize their locations. Household income is an interesting factor in this decision, since it oscillates back and forth between different income groups. In terms of one's level of payment, model results suggest that older persons and Caucasians are more willing to pay than those with a driver's license or those in households with more children.

Table 10: Model Estimation Results for WTP to Anonymize Location While Using SAVs

Selection Model		
Independent Variables	***Coefficients***	***T-stat***
Constant	-0.40	-1.61
Concerned about privacy?	1.73	9.26
No disability?	-0.69	-5.75
Household owns 1 vehicle?	0.60	5.40
2 vehicles?	0.67	5.48
3 vehicles?	0.63	4.64
4+ vehicles?	0.66	4.14
Household size equal to 2?	0.16	2.02
equal to 3?	0.27	2.67
equal to 4+?	-0.11	-1.13
Household workers equal to 1?	-0.12	-1.54
equal to 2?	-0.10	-1.07
equal to 3?	-0.47	-3.14
equal to 4+?	-0.51	-1.89
Age of respondent (in years)	-0.02	-11.14
Is Male?	-0.35	-6.35
Household income: < $20,000	0.72	5.51
Or < $30,000	0.13	1.06
Or < $40,000	-0.02	-0.14
Or < $50,000	0.18	1.31
Or < $60,000	0.17	1.19
Or < $75,000	0.33	2.41
Or < $100,000	0.25	1.87
Or < $125,000	0.17	1.19
Or < $150,000	0.68	3.96
Or < $200,000	0.14	0.84
Or > $200,000	0.70	4.06
Exponential Regression Model		
Independent Variables	***Coefficients***	***T-stat***

Table 10: Model Estimation Results for WTP to Anonymize Location While Using SAVs

Constant	-0.86	-7.23
Age of respondent (in years)	-0.4E-2	-3.24
Have U.S. driver's license?	0.26	3.72
Caucasian?	-0.14	-3.10
Household has 2 or less children?	0.48	6.11
Household income: < $20,000	0.23	2.45
Or < $30,000	0.52	5.20
Or < $40,000	0.39	3.67
Or < $50,000	0.18	1.77
Or < $60,000	0.08	0.72
Or < $75,000	0.41	4.07
Or < $100,000	0.38	3.94
Or < $125,000	0.38	3.60
Or < $150,000	0.36	3.22
Or < $200,000	0.54	4.52
Or > $200,000	0.06	0.56
Population density (per square mile)	-0.2E-4	-3.13
Employment density (per square mile)	0.1E-4	2.48
Variables with Heteroscedasticity		
Age of respondent (in years): Exponential model	-0.6E-2	-16.62
Fit statistics		
Final log-likelihood	-705.4893	
Pseudo R-square	0.6140	
Likelihood Ratio Chi-Square	2244.21	
Number of observations	2,588	

The changes in responses and marginal expected value of WTP is calculated for this model similarly to the previous hurdle model and is illustrated in Figure 2. The percentage deviation of the expected value of WTP helps identify potential policy impacts to privacy and location anonymization decisions. Negative changes on all covariates showed that, although Americans seem to want privacy and may be willing to pay for anonymized trips, it may be unlikely that privacy of trip locations will be a concern in the future. They also suggest that, moving forward, with the aging population and increasing average wages, there may be a decline in the dollar amount that Americans are willing to pay to anonymize a trip.

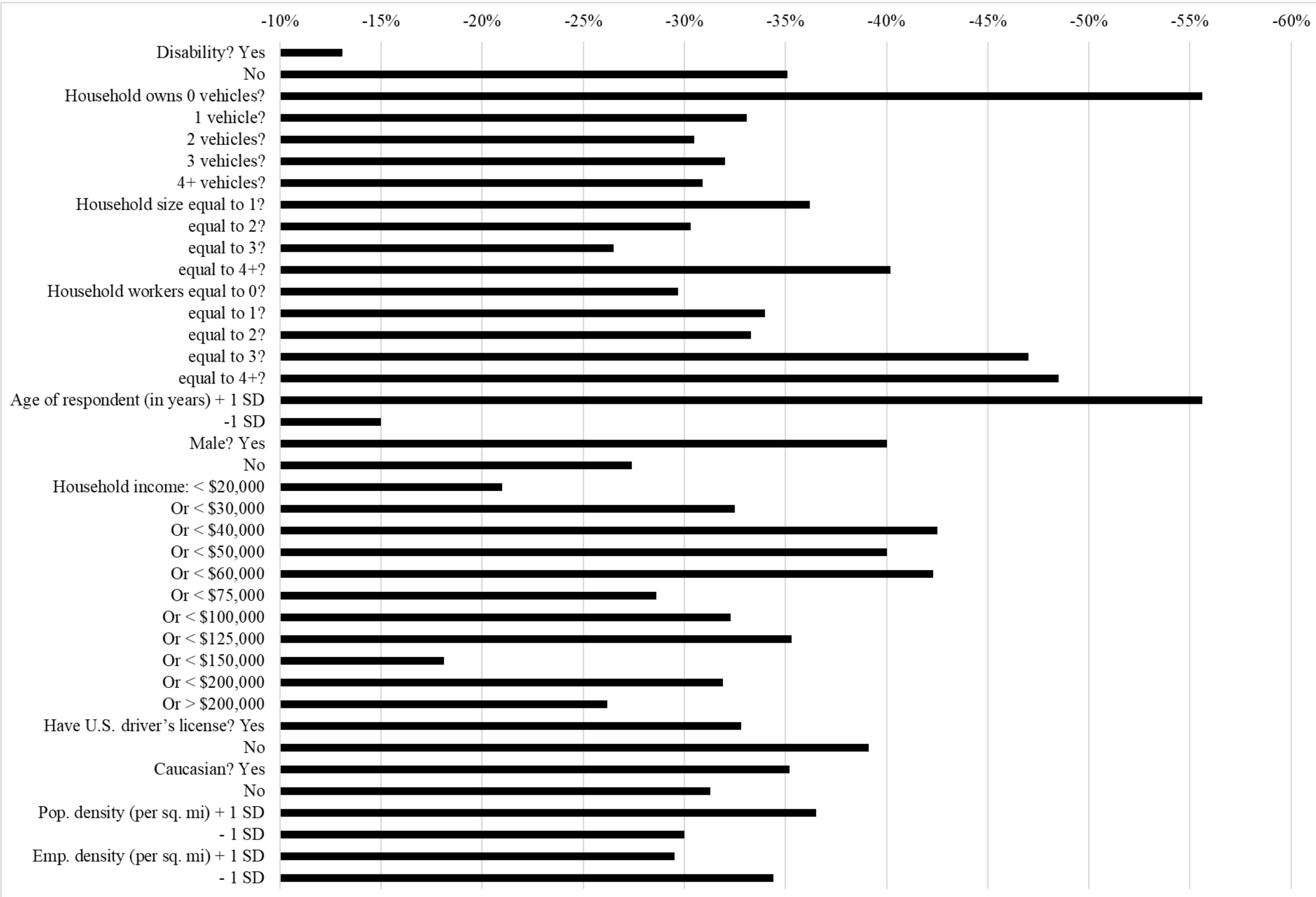

Figure 2: Covariate elasticities for WTP to Anonymize Location in an SAV

Long-Distance Mode Choice with AVs and SAVs

Mode choice for long-distance travel was studied by estimating a multinomial logit model when AVs and SAVs are available. Correlation is allowed between responses from the same respondent and an independent identically distributed Gaussian error term was assumed for observations between different respondents. The model developed shed some interesting inferences.

The estimated coefficients for this scenario are shown in Table 11. SAVs seem to be a dominating choice for business travel relative to personal travel and relative to the other modes. Personal AVs and conventional vehicles may be preferred for personal travel. Distance seems to only play a vital part in deciding to choose to fly. Current vehicle ownership does indicate that one may be less interested in AVs and SAVs, however, these are still competing modes when other factors come into play. Older people still seem to prefer the private car as the most preferred alternative with AVs as their next choice, when everything else is constant. Having a current driver's license also deters people from using these automated modes. Regardless of the household's income bracket, there seems to be wide consensus in favoring SAVs as they are expected to turn out to be the most affordable alternative.

Table 11: Model Estimation for Future Mode Choice in Long-Distance Travel with AVs and SAVs

Multinomial Logit Model			
Alternatives (Base Case – Private Car)	**AVs**	**SAVs**	**Airplane**
Independent Variables	***Coefficient (T-stat)***	***Coefficient (T-stat)***	***Coefficient (T-stat)***
Constant	1.79 (1.67)	-0.48 (-0.34)	1.92 (1.49)
Trip Type – Personal?	(base)		
– Business?	-0.03 (-0.15)	1.23 (4.83)	0.56 (3.22)
– Recreation?	-0.06 (0.78)	0.15 (0.86)	0.16 (1.94)
Distance: 100 – 500 miles	(base)		
> 500 miles	0.10 (0.86)	0.05 (0.29)	1.55 (10.45)
Household owns 1 vehicle?	-0.84 (-1.23)	-0.36 (-0.45)	0.20 (0.27)
2 vehicles?	-1.27 (-1.85)	-0.24 (-0.28)	-0.21 (-0.27)
3 vehicles?	-0.65 (-0.88)	0.41 (0.44)	-0.26 (-0.31)
4+ vehicles?	-0.72 (-0.83)	0.26 (0.26)	-0.80 (-0.91)
Household size equal to 2?	0.91 (2.21)	0.42 (0.74)	-0.37 (-0.79)
equal to 3?	0.12 (0.21)	-0.23 (-0.29)	-0.01 (-0.01)
equal to 4+?	-0.25 (-0.33)	-0.51 (-0.48)	-0.21 (-0.31)
Household workers equal to 1?	-0.45 (-1.20)	-0.97 (-1.82)	-0.97 (-2.29)
equal to 2?	-0.30 (-0.69)	-0.32 (-0.49)	-0.12 (-0.25)
equal to 3?	-0.59 (--0.84)	-1.40 (-1.61)	-0.94 (-1.30)
equal to 4+?	0.75 (0.60)	-0.72 (-0.46)	0.07 (0.05)
Age of respondent (in years)	-0.02 (-2.14)	-0.03 (-1.92)	-0.03 (-2.63)
Have U.S. driver's license?	-2.41 (-3.85)	-2.26 (-3.30)	-1.88 (-2.31)
Caucasian?	-0.26 (-0.81)	-1.01 (-2.41)	-0.75 (-2.12)
Children in the household: 1 child?	0.50 (1.05)	0.90 (1.48)	-0.96 (-2.07)

Table 11: Model Estimation for Future Mode Choice in Long-Distance Travel with AVs and SAVs

2 children?	1.35 (1.75)	0.89 (0.86)	-0.68 (-1.01)
3 children?	2.30 (2.42)	1.87 (1.59)	0.21 (0.23)
4+ children?	-0.43 (-0.37)	0.19 (0.15)	-1.10 (-1.27)
Household income: < $20,000	0.78 (1.06)	1.75 (1.35)	0.34 (0.29)
Or < $30,000	0.94 (1.27)	3.21 (2.63)	-0.21 (-0.22)
Or < $40,000	0.69 (1.00)	2.98 (2.48)	0.22 (0.25)
Or < $50,000	0.20 (0.32)	2.37 (2.04)	0.79 (0.90)
Or < $60,000	1.76 (2.32)	4.84 (3.83)	0.88 (0.90)
Or < $75,000	1.35 (1.87)	1.75 (1.42)	1.43 (1.53)
Or < $100,000	0.83 (1.17)	3.72 (3.16)	1.50 (1.60)
Or < $125,000	1.51 (2.20)	3.75 (3.27)	2.03 (2.23)
Or < $150,000	1.62 (1.99)	3.10 (2.50)	2.30 (2.29)
Or < $200,000	1.74 (2.22)	2.41 (1.87)	2.29 (2.50)
Or > $200,000	1.41 (1.72)	2.60 (2.04)	2.11 (2.08)
Has attended some college?	0.23 (0.80)	0.89 (2.12)	0.75 (2.61)
Currently working at least part-time?	1.52 (3.07)	1.34 (2.02)	1.36 (2.34)
Single?	0.49 (2.17)	0.12 (0.37)	0.17 (0.65)
Population density (per square mile)	0.2E-4 (0.65)	0.5E-4 (1.24)	0.4E-4 (1.53)
Employment density (per square mile)	-0.5E-4 (-0.96)	-0.1E-4 (-1.06)	-0.8E-4 (-1.59)
Fit statistics			
Number of observations (number of respondents)		9,257 (2,005)	
F-test (114, 1891)		5.74	
Prob > F		0.00	

The expected change in mode shares for all the modes discussed above are calculated for changes in each of the covariates. This is done by identifying the expected value of the mode share at the new mean value of the covariate after shifting it by one standard deviation (or one indicator level for discrete variables). This helps see the practical effect of each covariate on future mode share. Figure 3 shows the percentage change in mode-shares with respect to the previously determined share and gives an idea of the impact of each of the covariates. As evaluated from the coefficients previously, the absence of children may have a deep impact in choosing to fly compared to the other modes for LD travel. There may be a 67% increase in SAVs' mode-share mainly due to business travel. Absence of vehicle in the household at present also seems to favor use of personal AVs for future LD travel. Interestingly, households with 3+ vehicles at present shows a 52% increase in choosing SAVs, likely from large family sizes with members accustomed to sharing their ride. Households with few (up to 3) children and significant number of workers may prefer AVs for their LD travel. Interest in SAVs is spread out through all income groups while results suggest that some income brackets may not use SAVs for their LD needs, which is quite interesting. Single people seem to prefer to fly, and households with two or more members show a tendency to prefer AVs and SAVs.

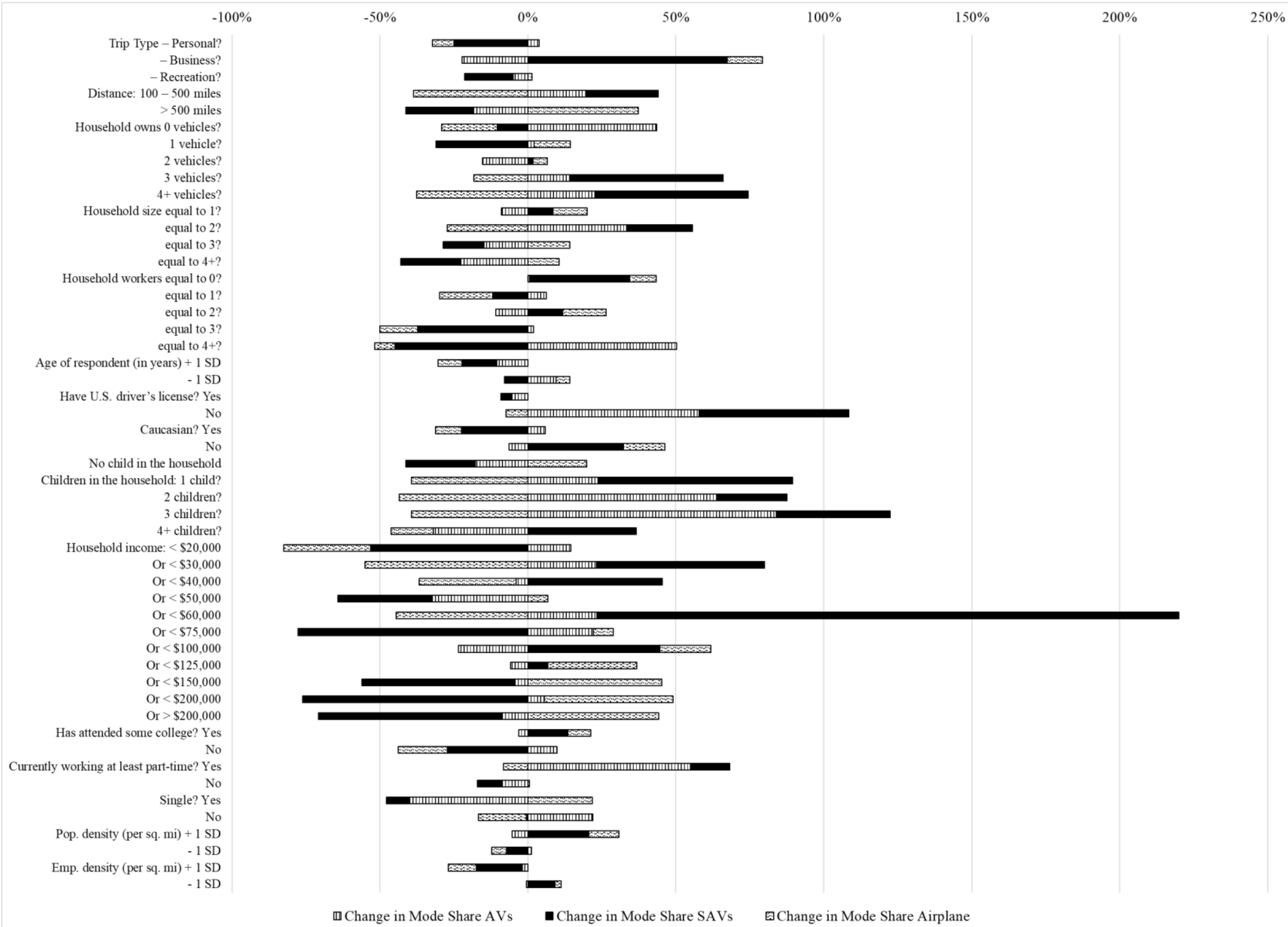

Figure 3 Covariate Elasticities for Future Mode Choice in Long-Distance Travel

CONCLUSIONS

This study builds on gaps in past public AV-perception studies by emphasizing ethics, privacy, the nuances of dynamic ride-sharing (with strangers in SAVs), and long-distance trip shifts. AVs and SAVs are still emerging, and perceptions will evolve as providers deliver more demonstrations and first-hand experiences. In the meantime, policymakers, producers, planners and engineers can all benefit from a sense of what Americans and others expect to do with such technologies.

Dynamic ride-sharing preferences among adults were assessed in detail here and provided valuable insights. A hurdle model to predict this WTP during the day suggests added travel time to a shared trip did not influence WTP after a person is willing to share their ride, which is in line with findings by Lavieri and Bhat (2019). SAV service boasting low added travel time on shared rides can attract several riders, and when used in tandem with smart pricing to cater to the distribution of WTP, it can be an effective service. Practical significance was analyzed by changing the average respondent's covariate. An aging population can decrease interest in DRS, meaning the future of the service lies almost entirely in the younger generation. Policymakers should cater to this target audience to maximize benefits. Eventually, phasing out driver licensure can also help improve SAV use and increase DRS. Higher employment densities or household incomes may increase WTP by 21% and 26%, respectively, meaning higher WTP is nearly inevitable with an improving economy. Few respondents appear willing to use DRS at night, but background checks on riders can help increase ridership.

Greater levels of concern emerge when privacy is the focus of a survey question, rather than as one among many potential issues to be selected by a respondent. A hurdle model developed for WTP to anonymize location while using AVs indicated that, at present, there were many indicators alluding toward privacy concerns (like age, number of children in the household, vehicle ownership and income). However, an elasticity analysis revealed that this may not be true in the future. Change in all of the covariates led to a decrease in the expected WTP indicating that this may soon not be an issue. However, this bold claim warrants a more elaborate privacy study, though it is beyond the scope of this paper.

Crash ethics, although not modeled, were investigated, using three targeted questions based on different crash scenarios. Americans feel that any AV, when having no choice but to crash into one or more pedestrians or vehicles should not change its trajectory (to select a different pedestrian or vehicle to crash into), even if the current trajectory does not minimize overall harm. They expect this to be left to chance and believe that AV manufacturers must be held accountable. The future of insurance companies may change drastically if this is mandated by governments.

Americans expect much of their long-distance travel (for trips over 50 miles, one-way) to shift toward AVs and SAVs. For example, nearly 50% of trips between 50 and 500 miles (one-way) are expected to eventually take place in an AV or SAVs, however, this is slightly lower than LaMondia *et al.*'s (2016) prediction of around 55%, on average for these ranges showing a shift in perceptions. A multinomial logit for long-distance mode choices in the presence of affordable AVs and SAVs, suggests that Americans prefer SAVs, irrespective of their household's income, ceteris paribus. Some business travel under 500 miles is also expected to be completed using SAVs. Older people are estimated to prefer to use their own vehicles, now and in the future. Shifts in mode splits were also examined. For example, SAV share for long-distance trips rises by 67% when the average long-distance traveler is traveling for business. Work-centric households (more than average number of workers in the household) may prefer to own AVs more than other households. Middle-class households may be greatly inclined towards SAVs (196% increase in share if the average respondent was earning between $75k and $120k). The aviation sector may wish to adjust its investments and future marketing strategies in response to changes in market share for long-distance travel.

These results suggest that Americans are not yet very confident about AV use, but expect to develop heavy usage levels. WTP, demand levels, perception and public opinion are helpful to transportation planners and policymakers, technologists and vehicle manufacturers, fleet managers and system operators, as well as airlines, land developers, attorneys, insurers, and the tourism industry. Regular survey efforts help nations and regions, companies and public agencies, better prepare for the coming paradigm shifts, hopefully with equity, environment, and efficiency in mind. The limitation to keep the survey relatively brief meant that some other new innovative questions were removed before final dissemination. Upcoming surveys should consider inquiry into new AV and SAV design in the absence of a driver. Ride-sourcing companies do not allow users to rate those in their shared rides. Screening based on an existing social connection (e.g., via Facebook or LinkedIn), or satisfying a criminal background check may help with shared rides. Future work can tackle such aspects of SAVs and DRS. Additionally, in the realm of DRS, acceptable waiting times can be assessed instead of forcing a pre-determined waiting time on the respondent for WTP questions.

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