ASSESSING PUBLIC OPINIONS OF AND INTEREST IN NEW VEHICLE TECHNOLOGIES: AN AUSTIN PERSPECTIVE

Prateek Bansal
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
prateekbansal@utexas.edu
Phone: 512-293-1802

Kara M. Kockelman
(Corresponding Author)
E.P. Schoch Professor in Engineering
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
kkockelm@mail.utexas.edu
Phone: 512-471-0210

Amit Singh
Graduate Research Assistant
Department of Civil, Architectural and Environmental Engineering
The University of Texas at Austin
amitsingh@utexas.edu
Phone: 512-232-3019

ABSTRACT

Technological advances are bringing connected and autonomous vehicles (CAVs) to the ever-evolving transportation system. Anticipating the public acceptance and adoption of these technologies is important. A recent internet-based survey was conducted polling 347 Austinites to understand their opinions on smart-car technologies and strategies. Ordered-probit and other model results indicate that respondents perceive fewer crashes to be the primary benefit of autonomous vehicles (AVs), with equipment failure being their top concern. Their average willingness to pay (WTP) for adding full (Level 4) automation ($7,253) appears to be much higher than that for adding partial (Level 3) automation ($3,300) to their current vehicles.

This study estimates the impact of demographics, built-environment variables, and travel characteristics on Austinites' WTP for adding such automations and connectivity to their current and coming vehicles. It also estimates adoption rates of shared autonomous vehicles (SAVs) under different pricing scenarios ($1, $2, and $3 per mile), choice dependence on friends' and neighbors' adoption rates, and home-location decisions after AVs and SAVs become a common mode of transport. Higher-income, technology-savvy males, living in urban areas, and those who have experienced more crashes have a greater interest in and higher WTP for the new technologies, with less dependence on others' adoption rates. Such behavioral models are useful to simulate long-term adoption of CAV technologies under different vehicle pricing and demographic scenarios. These results can be used to develop smarter transportation systems for more efficient and sustainable travel.

Keywords: Connected and Autonomous Vehicles; Shared Autonomous Vehicles; Willingness to Pay; Ordered Probit Models.

1. INTRODUCTION AND MOTIVATION

Car travel is relatively unsafe, costly, and burdensome. Roughly 2.2 million Americans are injured in crashes each year, resulting in over 30,000 fatalities (NHTSA 2014b). The economic cost of these crashes is roughly $300 billion, which is approximately three times the U.S.'s annual congestion costs (Cambridge Systematics 2011). Connected-autonomous vehicles (CAVs) provide a solution to the burden of car travel, and have the potential to reduce a high proportion of the 90% of crashes that result from driver error (NHTSA 2008). CAVs are the biggest technological advances in personal transport that the world has seen in over a century, with a promising future of safer and more convenient transportation.

CAVs are no longer a fantasy, and may soon become a daily mode of transport for hundreds of millions of people. Several mainstream companies such as Google, Toyota, Nissan, and Audi are developing and testing their own prototypes (Smiechowski 2014). With rapid advances in vehicle automation and connectivity, the U.S. National Highway Traffic Safety Administration (NHTSA 2013 & 2014a) has recognized key policy needs for CAVs. California, Nevada, Florida, and Michigan states have legislation to allow AV testing on public roads (Schoettle and Sivak 2014a). Navigant Research (2014) estimated that 75% of all light-duty-vehicle sales around the globe (almost 100 million annually) will be autonomous-capable by 2035. In accordance with this timeline, Litman (2014) expects that AVs′ beneficial impacts on safety and congestion are likely to appear between 2040 and 2060. If AVs prove to be very beneficial, Litman (2014) suggests that human driving may be restricted after the 2060.

Successful implementation of CAV technologies will require public acceptance and adoption of these technologies over time, via CAV purchase, rental, and use (Heide and Henning 2006). In the past three years, many researchers (Kyriakidis et al. 2014, Schoettle and Sivak 2014a & 2014b, Underwood 2014) and consulting firms (J.D. Power. 2012, KPMG 2013, and Continental 2015) have conducted surveys and focus groups to understand the public perception about CAV's benefits and limitations. These studies provide descriptive statistics regarding public awareness, concerns, and expected benefits of smart-vehicle technologies, but they do not indicate how an individual's attributes (e.g., age, income, and education) and built-environment factors (e.g., employment density, population density, and area type) affect their opinions and willingness to pay (WTP) for such technologies.

This study designed and disseminated a survey for adult residents of Austin, Texas and received 358 completed responses. Those data facilitate a variety of perception and attitude analyses, using various econometric models. Response variables include respondents' WTP for Level 3 AVs, Level 4 AVs, and CVs; adoption rates of shared AVs under different pricing scenarios; adoption timing of CAV technologies; and home location decisions after AVs become a common travel mode. Motivations for each behavioral model are provided below.

Estimating an individual's or households' WTP for Level 3 AVs, Level 4 AVs, and CVs is useful in identifying the demographic characteristics and land use settings of early, as well as late, adopters. Such information helps policymakers and planners predict near-term to long-term adoption of CAV technologies and devise policies to promote optimal adoption rates.

While AVs are set to emerge on the public market, they may quickly offer another mode of transportation: shared autonomous vehicles (SAVs). SAVs offer short-term, on-demand rentals with self-driving capabilities, like a driverless taxi (Kornhauser et al. 2013, Fagnant et al. 2015). SAVs may overcome the limitations of current carsharing programs, such as vehicle availability, because travelers will have the flexibility to call a distant SAV Several studies (e.g., Burns et al. 2013, and Fagnant and Kockelman 2014) have shown how SAVs may reduce average trip costs by 30% to 85%, depending on the cost of automation and expected returns on the fleet operator's investment. Fagnant and Kockelman's (2015) agent-based simulation concluded that dynamic ridesharing (DRS) has the potential to further reduce total service times (wait times plus in-vehicle travel times) and travel costs for SAV users, even after incorporating extra passenger pick-ups, drop-offs, and non-direct routings. Chen et al. (2015) extended some of that work, and examined the performance (including profitability) of a fleet of shared electric AVs, across a 100-mile by 100-mile region. Pivoting off those simulations, this study explores the factors affecting SAV adoption rates under three pricing scenarios: \$1, \$2, and \$3 per occupied-mile traveled.

After AV adoption by neighbors and friends, individuals may gain confidence in such vehicles and/or sense social pressures, prompting them to purchase such technologies. Thus, this study estimates the adoption timing of AVs (e.g., will the respondent "never adopt" an AV, wait until 50% of his/her friends adopt an AV, or just 10% of his/her friends adopt one, or try to obtain an AV as soon as such vehicles are available in the market).

More efficient use of travel time (by allowing work or cell-phone conversations, for example) while riding in AVs may encourage individuals to shift their home locations to more remote locations, to enjoy lower land prices (and thereby bigger homes or parcels). Thus, AVs can exacerbate urban sprawl and increase a region's vehicle-miles traveled (VMT). However, a high-density of low-cost SAVs in downtown areas may counteract such trends. Given the major land use shifts that could occur, this study also explores the factors associated with residential shifts, as motivated by AV and SAV access. The following sections describe related studies, survey's design, many summary statistics, choice model specifications, key findings, and study conclusions.

2. LITERATURE REVIEW

This section summarizes the key findings of recent public opinion surveys about adoption of CAVs. Kyriakidis et al. (2014) conducted a survey of 5,000 respondents across 109 countries by means of a crowd-sourcing internet survey. Results indicate that respondents with higher VMT and who use the automatic cruise control feature in their current vehicles are likely to pay more for fully-automated vehicles. Approximately 20% of respondents showed a WTP of more than \$7,000 for Level 4 AVs, and approximately the same proportion of respondents did not want to pay more to add this technology to their vehicle. Most importantly, 69% of respondents expected that fully-automated vehicles are likely to gain 50% market share by 2050.

Schoettle and Sivak (2014a) surveyed 1,533 respondents across the U.K., the U.S., and Australia to understand their perception about AVs. Results indicate that approximately two-thirds of respondents had previously heard about AVs. Interestingly, 25% respondents were willing to spend at least $2,000 to add full self-driving automation in the US, while same proportion of respondents in the UK and Australia were willing to spend $1,710 and $2,350, respectively. However, 54.5% respondents is the U.S., 55.2% in the U.K., and 55.2% in Australia did not want to pay more to add these technologies. When asked about their activities (e.g., work, read, and talk with friends) while riding in Level 4 AVs, highest proportion, 41%, of respondents said they would watch the road even though they would not be driving. Results of one-way analysis of variance indicated that females are more concerned about AV technologies than males.

Underwood (2014) conducted a survey of 217 experts. Eighty percent of respondents had a master’s degree, 40% were AV experts, and 33% were CV experts. According to these experts, legal liability is the most difficult barrier to fielding Level 5 AVs (full automation without steering wheel), and consumer acceptance is the least. Approximately 72% of the experts suggested that AVs should be at least twice as safe as the conventional vehicles before they are authorized for public use. Fifty-five percent of the experts indicated that Level 3 AVs are not practical because drivers could become complacent with automated operations and may not take required actions.

J.D. Power (2012) conducted a survey of 17,400 vehicle owners before and after revealing the market price of 23 CAV technologies. Prior to learning about the market price, 37% of respondents showed interest in purchasing the AV technology in next vehicle purchase, but that number fell to 20% after learning that the this technology’s market price is $3000. 18 to 37 years old male respondents living in urban areas showed the highest interest in purchasing AV technology.

A KPMG (2013) focus group study, using 32 participants, notes that respondents became more interested in AVs when they were provided incentives like a designated lane for AVs, and learned their commute time would be cut in half. In contrast to Schoettle and Sivak’s (2014a) findings, the focus group’s discussion and participants’ ratings for AV technology suggests that females are more interested in these technologies than males. Continental (2015) surveyed 1,800 and 2,300 respondents in Germany and the United States, respectively. Approximately 60% of respondents expected to use AVs in stressful driving situations, 50% believed that AVs can prevent accidents, and roughly the same number indicated they would likely engage in other activities while riding in AVs.

Recently, Schoettle and Sivak (2014b) surveyed 1,596 respondents across the U.K, the U.S., and Australia to understand their perception about CVs. Surprisingly, only 25% of respondents had heard about CVs. When asked about the expected benefits of CVs, the highest proportion, 85.9%, of respondents expected fewer accidents and the lowest proportion, 61.2%, expected less distraction for the driver. Interestingly, 25% respondents were willing to spend at least $500, $455, and $394 in the U.S., the U.K, and Australia, respectively, to add CV technology.

However, 45.5%, 44.8%, and 42.6% of respondents did not want to pay anything extra to add these technologies in the U.S., the U.K., and Australia, respectively.

As mentioned above, these past studies reveal important information about individual perceptions of CAV technologies, but none has explored various related aspects, such as adoption rates of SAVs under various pricing scenarios, home-location choices when SAVs and AVs become common modes of transport, and peer-pressure effects on the adoption time of AVs. Moreover, econometric analysis is missing in all of these studies, but is crucial for devising efficient policies to increase market penetration of emerging transportation technologies. This study explores statistical and practical significance of relationships between respondents' demographics and built-environmental attributes, and their WTP for CAVs, adoption rates of SAVs, residence-shift decisions, and adoption timing of AVs using univariate and bivariate ordered probit (OP) models. These behavioral models will be very useful in forecasting adoption of CAV technology and land use changes under different pricing scenarios.

3. SURVEY DESIGN AND DATA PROCESSING

The data were collected via a survey in Austin, Texas from October to December 2014 using "Qualtrics", a web-based survey tool. Exploring respondents' preferences for adoption of emerging vehicle and transport technologies, the survey asked 52 questions regarding respondents' perceptions of AV technology upsides and downsides, ridesharing, and carsharing. Respondents were also asked about their WTP for CAVs, adoption rates of SAVs in different pricing scenarios, future home-location decisions, adoption timing of AVs, current travel patterns, and demographics.

Austin neighborhood associations were first contacted via email and passed the survey requests to their respective residents. A total of 510 respondents initiated the survey; only 358 of them completed it. However, 11 of those were not Austinites and so were excluded from the sample, resulting in a total sample of 347 adults (over 18 years of age). The sample over-represented women, middle-aged persons (25-44 years old) and those with a bachelor's degree or higher. Therefore, the survey sample proportions in each demographic class were scaled using the 2013 American Community Survey's Public Use Microdata Sample (PUMS 2013) for the Austin. The population weights were calculated by dividing the sample into 72 categories based on gender, age, education and household income. To understand the impact of built-environment factors (e.g., employment density, population density, and area type) on preferences, respondents' home addresses were geocoded[1] using Google Maps API and spatially joined with Austin's traffic analysis zones (TAZs) using open source Quantum GIS.

4. DATA SET STATISTICS

Table 1 summarizes the demographic, built-environment, zone-level[2], and technology-related variables after correction for biased-sample's demographics. This study uses these variables as

[1] For respondents, who did not provide their street address or recorded incorrect addresses, their internet protocol (IP) locations were used as the proxies for their home locations.
[2] The TAZ-level variables were obtained by spatial mapping of respondents' home locations with a TAZ-level shape files, obtained from Austin's Capital Area Metropolitan Planning Organization.

the predictors in many model specifications. Prior to using these predictors, each respondent's record was population-weighted to provide relatively unbiased model calibration.

4.1 Current Technology Awareness

To better understand the future adoption of smart transportation technologies and strategies, it is important to explore respondents' current awareness about them. Table 1 indicates that in general, Austinites are tech-savvy; 92% of the population-weighted sample carry or own a smartphone, 80% have heard of Google's self-driving car, and 60% consider anti-lock braking systems (ABS, required on all cars sold in the U.S. since September, 2011) to be a form of vehicle automation (which it is: Level 1 automation). Probably, due to popularity of carsharing (Car2Go and Zipcar) and ridesharing (UberX and Lyft) companies in Austin, 95% and 85% of respondents are familiar with both of them, respectively.

Table 1: Population-weighted Summary Statistics of Explanatory Variables (N_{obs}=347)

Type	Explanatory Variables	Description	Mean	SD	Min.	Max.
Demographic & Built-environment Predictors	Drive alone for work trips	Indicator for drive alone	0.49	0.50	0	1
	Drive alone for social trips	Indicator for drive alone	0.29	0.45	0	1
	Distance from workplace	Miles	4.75	5.37	0.50	17.50
	Distance from downtown	Miles	6.75	5.08	0.50	17.50
	Gender	Indicator for Male	0.50	0.50	0	1
	U.S. driver license	Indicator for having driving license	0.98	0.13	0	1
	Number of children	Per household	0.40	0.80	0	5
	Education level	Indicator for bachelor's degree	0.59	0.49	0	1
	Employment status	Indicator for Full-time worker	0.59	0.49	0	1
	Age	Years	36.58	15.72	21	70
	Annual VMT	Miles	9,578	5,631	2500	22,500
	Annual household income	$ per year	59,453	44,178	5,000	250,000
	Household size		2.57	1.41	1	7
	Number of past crash experiences		1.62	1.38	0	5
Zone-level Predictors	Population density	Persons per square miles	6,096	6,074	0	38,945
	Household density	Households per square miles	3,040	3,055	0	18,620
	Total employment density	Persons per square miles	7,435	17,472	0	110,596
	Basic employment density	Persons per square miles	231.92	747.66	0	7,658
	Retail employment density	Persons per square miles	827.03	1,501	0	11,219
	Service employment density	Persons per square miles	2,101	9,216	0	85,841
	Area type	Indicator for Urban areas	0.87	0.33	0	1
	Median household income	$ per year	49,289	37,717	0	248,203
Tech-based Predictors	Have heard about Google	Indicator for who have heard…	0.80	0.40	0	1
	ABS form of automation	Indicator for who think…	0.59	0.49	0	1
	Carry smartphone	Indicator for who carry…	0.92	0.27	0	1
	Familiar with carsharing	Indicator for familiarity with…	0.95	0.21	0	1
	Familiar with UberX or Lyft	Indicator for familiarity with…	0.88	0.32	0	1

4.2 Key Response Variables

Table 2 summarizes the key response variables estimated in this study. At cost of more than $5,000, 24% and 57% of respondents were willing to add Level 3 and Level 4, respectively, to their next vehicle purchase. As expected, the average WTP (of the population-corrected sample) for Level 4 automation ($7,253) is much higher than that for Level 3 automation ($3,300). Apparently, AVs may not impact residential land-use patterns much, since 74% of respondents expect to stay at their current location even after AVs and SAVs become common modes of transport[3]. 30% showed interest in using AVs as soon as they are available for mass market sales in the U.S. Interestingly, approximately half of the respondents would prefer their family, friends, or neighbors to use AVs prior to their adoption. Only 15% and 3% of respondents expected to use SAVs once a week at a cost of $2 per mile and $3 per mile, respectively[4]. Reponses like these imply that most respondents are not willing to spend more for SAV use than what UberX & Lyft charge (about $1.50 per mile). However, with social acceptance of AVs and the reliability of SAVs for longer-distance trips, future SAVs costs may fall. At a cost of $1 per mile, 41% of respondents expected to use SAVs at least once a week. Only 26% of respondents rejected a proposal of adding connectivity[5] to their vehicles at a cost of less than $100.

Table 2: Population-weighted Results for Response Variables (N_{obs}=347)

Response Variables	Percentages	Response Variables	Percentages
WTP for Adding Level 3 Automation		**Residence-shift due to AVs**	
<$2,000	48%	Close to central Austin	14%
$2,000-$5,000	28%	Stay at the same location	74%
>$5000	24%	Farther from central Austin	12%
WTP for Adding Level 4 Automation		**Adoption Timing of AVs**	
<$2000	34%	Never	19%
$2,000-$5,000	18%	When 50% friends adopt	26%
$5,000-$10,000	19%	When 10% friends adopt	25%
>$10,000	28%	As soon as available	30%
WTP for SAVs ($1/mile)		**WTP for SAVs ($2/mile)**	
Rely less than once a month	35%	Rely less than once a month	57%
Rely at least once a month	24%	Rely at least once a month	28%
Relay at least once a week	28%	Relay at least once a week	12%
Relay entirely on SAV fleet	13%	Relay entirely on SAV fleet	3%
WTP for SAVs ($3/mile)		**WTP for Adding CV Technology**	
Rely less than once a month	70%	Not interested	26%
Rely at least once a month	26%	Neutral	19%
Rely at least once a week	2.1%	Interested	55%
Rely entirely on SAV fleet	1.9%		

4.3 Other Opinions about AVs and CVs

[3] Prior to asking a question about residence-shift decisions, respondents were informed that self-driving vehicles will make travel much easier for many people. By being able to sleep on the road, some travelers may decide to live farther from the city center, their workplaces, their children's schools, or other destinations (in order to access less expensive land for a larger home or parcel, for example). On the other hand, by living in more urban locations, one will be able to more quickly (and less expensively) access a shared fleet of self-driving vehicles (at a rate of say, $1.50 per mile of travel), allowing them to let go of cars they presently own, and turn to other transport options.

[4] Before asking about respondents' adoption rates of SAVs in different pricing scenarios, they were informed that the taxis in Austin presently cost about $2.50 to $3.50 per mile of travel, UberX and Lyft currently charge about $1.50 per mile of travel, and Car2Go charges $0.80 to $1.25 per mile, within its operating geographic area (and $15 per hour for parking outside geographical area).

[5] Before asking about WTP for CVs, respondents were advised that connectivity can be added to an existing vehicle, requiring one's smartphone plus extra equipment (a DSRC chip and inertial sensor) costing less than $100.

Table 3 summarizes the individuals’ perceptions about the benefits and concerns of CAVs. 19% of respondents were not at all interested in owning Level 4 AVs. Respondents indicated three main issues regarding AVs: 50% of respondents were concerned about equipment or system failure, while 48% and 38% were concerned about interactions with conventional vehicles and affordability, respectively. Only 7% of respondents were apprehensive about learning to use AVs. 31% of respondents believe that AVs cannot help with calming congestion, making this the “least likely” AV benefit (among plausible options tested). When asked about the other three benefits (fewer crashes, lower emission, and better fuel economy), respondents considered them almost equally likely, but a reduction in crashes received maximum (63%) support. 75% of respondents indicated wanting to talk or text with friends and look out of the window while riding in AVs – making these the two most appealing tasks for respondents while traveling in Level 4 AVs. More than 70% of respondents would like to ride in AVs on freeways, high-speed highways, and congested traffic, while only 46 % would let the vehicles drive themselves on city streets. Surprisingly, only 47% of respondents have heard about CVs. It is worth noting that only 4.3% of respondents are currently surfing internet and 6.2% are emailing while driving (conventional vehicles), but 31.7% and 39% are interested in adding these technologies to their vehicles, respectively.

Table 3: Population-weighted Results for Opinion-based Questions on AVs and CVs (N_{obs}=347)

Type	Opinion-based questions	Not interested	Slight interested	Very interested
	Interest in having Level 4 AVs	19%	40%	41%
Concerns with Level 4 AVs		**Very worried**	**Slightly worried**	**Not worried**
	Equipment or system failure	50%	38%	12%
	Legal liability for drivers or owners	36%	42%	22%
	Hacking the vehicle’s computer systems	30%	44%	26%
	Traveler’s privacy disclosure	31%	39%	30%
	Interactions with conventional vehicles	48%	33%	19%
	Learning to use self-driving vehicles	6.9%	29.1%	64%
	Affordability of a self-driving vehicle	38%	39%	23%
Benefits of Level 4 AVs		**Very likely**	**Somewhat likely**	**Unlikely**
	Fewer crashes	63%	26%	11%
	Lesser traffic congestion	45%	24%	31%
	Lower vehicle emissions	48%	40%	12%
	Better Fuel Economy	58%	32.8%	9.2%
Tasks while Riding AVs		**Yes**	**No**	
	Text or Talk	74%	26%	
	Sleep	52%	48%	
	Work	54%	46%	
	Watching movies or play games	46%	54%	
	Look out the windows of the vehicle	77%	23%	
Like to Ride AVs		**Yes**	**No**	
	Along freeways or highways	73%	27%	
	Along city streets	46%	54%	
	In congested traffic	70%	30%	
		Yes	**No**	

Opinion about CV Technology	Have heard of CVs	53%		47%
		Already using	**Interested**	**Not interested**
	Internet surfing via an in-built car screen	4.3%	31.7%	64%
	Reading and dictating email while driving	6.2%	39%	54.8%
	operating phone via steering wheel control	12%	48%	40%

5. MODEL ESTIMATION

This study estimated adoption rates of SAVs under three pricing scenarios ($1, $2, and $3 per mile), interest in having one's existing vehicle become a CV (for under $100), adoption timing of AVs, and future home-location shifts (after AVs and SAVs become common modes of transport) using univariate OP specifications in Stata 12 software (Long and Freese 2006). The univariate OP model specifications are presented here in the context of interest in adding connectivity. The main equation for this specification is as follows (Greene 2012):

$$y_i^* = \beta' x_i + \varepsilon_i \qquad (1)$$

where, subscript 'i' denotes an individual observation, y_i^* represents the individual's latent inclination to add connectivity at a cost of less than $100, x_i represents a vector of covariates for each individual, β' represents a vector of regression coefficient, which are to be estimated, and ε_i represents a random error term assumed to follow a standard normal distribution.

For this example, two thresholds (μ_1 through μ_2) were estimated to distinguish the three categories; where μ_1 represents the threshold between "not interested" and "neutral" and μ_2 is the threshold between "neutral" and "interested in adding connectivity at a cost of less than $100". Under this specification, the opinion probabilities are as follows:

$$\Pr(\text{not interested}) = \Pr(y_i^* \le \mu_1) \qquad (2)$$
$$\Pr(\text{neutral}) = \Pr(\mu_1 \le y_i^* \le \mu_2) \qquad (3)$$
$$\Pr(\text{interested}) = \Pr(y_i^* \ge \mu_2) \qquad (4)$$

The WTP for AVs (Level 3 and Level 4) had two related response variables and so were jointly estimated using seemingly unrelated specifications[6] of the bivariate OP model[7] (as described in Sajaia [2008]).

Initial model specifications included all Table 1's explanatory variables. The models were re-estimated using stepwise elimination by removing the covariate with the lowest statistical significance until all p-values were less than 0.32, which corresponds to a |Z-stat| of 1.0. Although most of the explanatory variables enjoy a p-value greater than .10 (|Z-stat| > 1.645), it

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[6] In seemingly unrelated specifications, error terms are only correlated across choices of the individual, but are independent and homoscedastic across the individuals.

[7] To estimate WTP for SAVs, complex trivariate OP model specifications could be used, but it would have only slightly improved statistical significance of predictors, without affecting the magnitude and sign of the coefficients much. Therefore, to control the complexity, three univariate OP models were estimated for each of the three cost scenarios ($1, $2, and $3 per mile).

was not used as a statistical significance threshold here, due to the slightly limited sample size (n=347). If more sample observations were available (say n=1000), statistical significance could have improved for many explanatory variables. Explanatory variables with p-value less than .01 (|Z-stat|>2.58) are considered highly statistically significant predictors.

Practical significance is generally more meaningful than statistical significance. This study considers an explanatory variable to be practically significant if a one-standard-deviation increment in it leads to a significant shift in the response variable. In this paper, response variables are probabilities of ordered choice options, so an explanatory variable is considered to be practically significant if the predicted probabilities (i.e., the ΔPr_i shown in Tables 4 through 8) change by more than a factor of 1.3 or less than a factor of 0.7. In other words, there is at least 30 percent shift in the predicted probability (which could be from 0.50 to 0.67 or to 0.35). If the shift in the model-predicted probability exceeds 50 percent (i.e., the ratio of the two is more than 1.5 or less than 0.50), the explanatory variable is defined here as *highly* practically significant. McFadden's R-Square[8] and adjusted R-square are also provided, to characterize all models' goodness of fit.

5.1 Willingness to Pay for AVs

Table 4 summarizes the bivariate OP model estimates of WTP for adding Level 4 automation (of less than \$2,000, \$2,000 to \$5,000, \$5,000 to \$10,000, or more than \$10,000) and WTP for Level 3 automation (less than \$2,000, \$2,000 to \$5,000, or more than \$5,000). Results indicate that male respondents with a greater number of children, living in higher- income neighborhoods, and who drive alone for social trips, ceteris paribus, are willing to pay more to add Level 3 and Level 4 automation to their next vehicle. In contrast, licensed drivers living in more jobs-sense neighborhoods, and who are familiar with carsharing and ridesharing companies are estimated to pay less to add Level 3 and Level 4 automation to their next vehicles, ceteris paribus[9]. Perhaps individuals who are familiar with carsharing and ridesharing would rather rely on low-cost SAVs instead of buying a new vehicle with added automation technology. Interestingly, individuals who travel more (exhibit higher annual VMT) and who live farther from their workplace exhibit higher WTP for adding Level 4 AVs, but lower WTP for Level 3 AVs. Perhaps the opposite signs, but practical significance of both attributes for the WTP of Level 3 and Level 4 AVs reflect the individuals' perception that they would be able to use their travel time (for work, sleep, or other meaningful activities) in a Level 4 AVs, but not in Level 3 AVs.

Table 4: Willingness to Pay for Autonomous Vehicles (Bivariate Ordered Probit Model Results)

Covariates (WTP for Level 4)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**	**ΔPr_4**
Number of past crash experiences	0.309	2.36	**-35.3%**	-12.4%	9.6%	**46.8%**
Familiar with carsharing (1=yes)	-1.149	-1.52	22.4%	1.7%	-8.4%	-21.6%
Familiar with UberX or Lyft (1=yes)	-1.400	-1.59	27.3%	1.3%	-14.6%	-23.7%

[8] McFadden's R-Square = $1-\frac{log(L_{full})}{log(L_{null})}$ and McFadden's adjusted R-Square = $1-\frac{(log(L_{full}))-n}{log(L_{null})}$, where n is the number of parameters in the fitted model, and L_{full} and L_{null} denote the likelihood values of the fitted model and only-intercept (with no explanatory variable) model, respectively.

[9] This study's finding about the relationship between respondents' gender and WTP for AVs are aligned with that of J.D. Power's (2012), and Schoettle and Sivak's (2014a) study. Similarly, Kyriakidis (2014) observed the positive correlation between income and WTP for AVs, which is quite intuitive.

Drive alone for work trips (1=yes)	0.616	1.72	-28.8%	-6.2%	7.5%	**31.1%**
Drive alone for social trips (1=yes)	0.833	2.28	-25.6%	-8.0%	8.6%	28.1%
Log(Annual VMT)	0.329	1.39	-20.2%	-15.7%	7.5%	**32.7%**
Distance from workplace (miles)	0.087	**2.96**	-22.3%	-13.9%	16.6%	27.3%
Gender (1=male)	0.442	1.28	-18.2%	-4.0%	5.7%	21.6%
U.S. driver license (1=yes)	-1.159	-1.36	18.3%	1.6%	-6.8%	-18.0%
Number of children	0.341	1.66	-15.5%	-16.4%	7.6%	21.7%
Age	-0.039	**-4.02**	**53.5%**	-12.4%	-21.5%	**-45.0%**
Total employment density (per mi^2)	-3.37E-04	-1.83	21.9%	3.7%	-8.2%	-21.2%
Median household income ($ per year)	7.29E-06	1.95	-23.8%	-15.8%	7.2%	**34.2%**
Thresholds	**Coef.**	**Std. Dev.**				
<$2,000 **vs.** $2,000 to $5,000	-7.401	0.386	--	--	--	--
$2,000-$5,000 **vs.** $5,000-$10,000	-6.514	0.299	--	--	--	--
$5,000-$10,000 **vs.** >$10,000	-5.503	0.447	--	--	--	--

Covariates (WTP for Level 3)	**Coef.**	**Z-stat**	**ΔPr$_1$**	**ΔPr$_2$**	**ΔPr$_3$**
Number of past crash experiences	0.217	1.59	-24.1%	11.0%	**32.4%**
Carry smartphone (1=yes)	0.708	1.18	-10.5%	5.3%	16.5%
Familiar with carsharing (1=yes)	-1.631	-1.37	20.1%	-15.9%	-20.1%
Familiar with UberX or Lyft (1=yes)	-1.203	-1.49	19.9%	-10.8%	-25.8%
Drive alone for work trips (1=yes)	0.539	1.46	**-31.4%**	28.1%	26.3%
Drive alone for social trips (1=yes)	1.102	**3.08**	-15.9%	18.4%	12.9%
Log(Annual VMT)	-0.470	-1.75	25.6%	-15.8%	**-33.1%**
Distance from workplace (miles)	-0.085	**-2.83**	22.8%	-14.5%	-27.4%
Gender (1=male)	0.507	1.48	-14.4%	5.8%	25.4%
U.S. driver license (1=yes)	-1.623	-1.77	16.3%	-8.6%	-24.8%
Number of children	0.485	2.32	-20.3%	8.9%	27.4%
Age	-0.031	-2.53	**35.6%**	-26.4%	**-37.3%**
Total employment density (per mi^2)	-2.30E-05	-2.11	16.2%	-8.6%	-24.7%
Median household income ($ per year)	8.26E-06	1.79	-18.9%	7.2%	**32.2%**
Thresholds	**Coef.**	**Std. Dev.**			
<$2,000 **vs.** $2,000 to $5,000	-8.865	0.488	--	--	--
$2,000-$5,000 **vs.** >$5,000	-7.323	0.373	--	--	--
Correlation coefficient: 0.921	**McFadden's R-Square:** 0.101	**McFadden's adjusted R-Square:** 0.061			

Notes: N_{obs}=347. "Log (Annual VMT)" was used as an explanatory variable in the model, but corresponding ΔPr's were calculated with respect to "Annual VMT". All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly statistically significant predictors. All ΔPr's with $|\Delta Pr_i|$ > 30% are in **bold,** and indicate practically significant predictors.

In addition, everything else equal, older persons are predicted to have a significantly lower WTP for AVs (in a practically and statistically significant sense). Perhaps they are concerned about learning to use AVs and do not trust these technologies. Practically significant and positive associations between the number of crashes experienced by an individual and their WTP for AVs indicates that such persons may be anticipating the safety benefits of AVs[10]. Respondents driving alone for work trips are estimated to have a (practically and statistically) significantly higher WTP for AVs, indicating the possibility of shifting commuters to SAV fleets in the future. A high correlation coefficient estimate across these two OP equations (ρ = +0.921) strongly supports the use of a seemingly unrelated bivariate OP specification here.

[10] As discussed earlier, the highest population-weighted proportion (63%) of respondents rated fewer crashes as a "very likely" benefit of AVs.

5.2 SAV Adoption Rates under Different Pricing Scenarios

Table 5 shows the OP model estimates of SAVs' adoption rates (i.e., relying on it less than once a month, at least once a month, at least once a week, or entirely on SAV fleet) in three pricing scenarios ($1 per mile [Model 1], $2 per mile [Model 2], and $3 per mile [Model 3]). Results indicate that full-time male workers living in urban areas, ceteris paribus, are likely to use SAVs more frequently, but consistent with the findings of the WTP for AVs' model, licensed drivers are estimated to use SAVs less frequently under all three pricing scenarios (everything else constant). Perhaps many licensed drivers are concerned about losing the excitement of driving after AVs become a common mode of transport[11]. Or they may have a hard time envisioning life without a privately held vehicle, and becoming largely reliant on SAVs. The practically significant positive associations of indicator variables (whether an individual has heard about Google's self-driving car and if an individual thinks that ABS is form of automation), in all three pricing-scenarios, suggests that tech-savvy individuals are likely to be frequent SAV users. Similarly, those living in denser neighborhoods expect higher SAV adoption rates (in all three models), perhaps due to less convenient parking facilities and lower vehicle ownership rates in these areas (Celsor and Millard-Ball 2007).

A highly practically significant and positive relationship between the home-distance from one's workplace and SAV adoption rates in Models 1 and 2 suggests that these workers are likely to use SAVs more often at current carsharing and ridesharing prices. Although this variable (respondents' distances from their workplace) does not appear in Model 3's final specification, another covariate, distance from downtown, may be capturing its effect[12]. The individuals living farther from downtown, all other attributes remaining constant, are expected to use SAVs less frequently at $3 per mile. Consistent with findings of the WTP for AVs' model, older persons are predicted to use SAVs less frequently, but individuals who have experienced more crashes in the past, ceteris paribus, have a practically significant inclination to use SAVs more frequently, even at $2 and $3 per mile (more than what carsharing companies and UberX or Lyft charge). The practical significance and negative association of the familiarity-with-carsharing indicator with SAV adoption rates in Models 2 and 3 suggests that individuals who already know carsharing's current price, may not be willing to pay more to use comparably convenient SAVs. A highly practically significant and negative relationship of an individual's annual VMT with SAV adoption rate (found only in Model 3) is as expected because SAVs at $3 per mile may lead to a high annual travel cost for these individuals.

Table 5: SAV Adoption Rates under Different Pricing Scenarios (Ordered Probit Model Results)

Covariates (Model 1: $1 per mile)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**	**ΔPr_4**
Have heard about Google car (1=yes)	1.835	**2.91**	**-32.6%**	-15.5%	26.1%	**58.1%**
ABS form of automation (1=yes)	0.903	2.54	**-37.9%**	-9.8%	**39.9%**	29.6%
Distance from workplace (miles)	0.126	**4.20**	**-49.6%**	-2.5%	**36.6%**	**63.7%**
Gender (1=male)	0.325	1.12	-10.6%	-3.0%	7.9%	18.2%
U.S. driver license (1=yes)	-1.267	-1.85	15.6%	2.7%	-11.9%	-20.9%
Number of children	-0.194	-1.25	12.4%	2.3%	-9.5%	-15.5%

[11] Litman (2014) anticipates that if AVs are successful, human driving could be restricted after 2060.

[12] The correlation coefficient of distance from work-place and distance from downtown is 0.53.

Employment status (1=full-time worker)	0.403	1.10	-11.3%	-3.2%	8.5%	20.5%
Area type (1=urban)	0.493	1.15	-13.0%	-3.8%	9.7%	15.6%
Population density (per mi^2)	2.59E-04	2.20	**-44.4%**	**-12.4%**	**32.3%**	**66.8%**
Households density (per mi^2)	-5.67E-04	-2.11	25.2%	-11.9%	-11.1%	-24.2%
Basic employment density (per mi^2)	-2.60E-04	-1.67	13.1%	6.4%	-10.0%	-26.6%
Thresholds	**Coef.**	**Std. Dev.**				
Will rely less than once a month **vs.** Will rely at least once a month	-0.043	0.577	--	--	--	--
Will rely at least once a month **vs.** Will rely at least once a week	1.246	0.122	--	--	--	--
Will rely at least once a week **vs.** Will rely entirely on SAV fleet	3.058	0.728	--	--	--	--
McFadden's R-Square: 0.120			**McFadden's adjusted R-Square:** 0.090			
Covariates (Model 2: $2 per mile)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**	**ΔPr_4**
Have heard about Google car (1=yes)	0.821	1.37	-15.3%	11.3%	**37.9%**	17.8%
ABS form of automation (1=yes)	0.940	**2.68**	-22.1%	**34.1%**	24.7%	23.3%
Number of past crash experiences	0.155	1.02	-9.5%	8.9%	28.6%	12.5%
Familiar with carsharing (1=yes)	-2.281	-1.25	22.8%	-22.4%	**-42.1%**	**-69.5%**
Distance from workplace (miles)	0.124	**2.94**	**-40.5%**	**51.7%**	21.7%	21.3%
Household size	0.310	1.97	-16.3%	18.5%	27.6%	17.4%
Gender (1=male)	0.690	2.00	-10.5%	13.0%	15.1%	18.2%
U.S. driver license (1=yes)	-1.432	-1.98	12.3%	-11.1%	-26.6%	-24.4%
Number of children	-0.542	-1.97	13.1%	-17.7%	-24.5%	-12.1%
Age	-0.014	-1.20	25.6%	**-39.2%**	-22.5%	-18.4%
Employment status (1=full-time worker)	0.839	2.28	-15.3%	19.7%	27.9%	16.3%
Area type (1=urban)	0.694	1.36	-11.9%	10.9%	23.4%	12.7%
Population density (per mi^2)	2.64E-04	2.14	-28.4%	35.3%	**45.1%**	19.6%
Households density (per mi^2)	-6.52E-04	-2.26	17.5%	-25.3%	-22.2%	-18.8%
Basic employment density (per mi^2)	-1.82E-04	-1.12	5.4%	-5.7%	-14.5%	-15.9%
Thresholds	**Coef.**	**Std. Dev.**				
Rely less than once a month **vs.** Rely at least once a month	-1.275	0.625	--	--	--	--
Rely at least once a month **vs.** Rely at least once a week	0.468	0.448	--	--	--	--
At least once a week **vs.** Rely entirely on SAV fleet	2.425	0.819	--	--	--	--
McFadden's R-Square: 0.129			**McFadden's adjusted R-Square:** 0.079			
Covariates (Model 3: $3 per mile)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**	**ΔPr_4**
Have heard about Google car (1=yes)	1.473	2.21	-10.7%	25.1%	18.0%	**36.4%**
ABS form of automation (1=yes)	1.431	**3.28**	-20.3%	**51.7%**	29.5%	17.2%
Number of past crash experiences	0.183	1.23	-11.3%	29.2%	**32.9%**	23.6%
Familiar with carsharing (1=yes)	-1.948	**-3.05**	15.3%	**-39.4%**	-21.7%	**-34.7%**
Annual VMT	-5.32E-05	-1.65	20.3%	**-52.3%**	-17.8%	-10.8%
Distance from downtown (miles)	-0.064	-1.63	10.3%	-22.7%	-22.9%	-26.1%
Gender (1=male)	0.658	1.76	-8.1%	17.8%	14.3%	15.9%
U.S. driver license (1=yes)	-1.864	-2.56	12.1%	-28.2%	-12.1%	-16.2%
Age	-0.029	-2.30	10.2%	-21.8%	-11.5%	-12.5%
Employment status (1=full-time worker)	1.022	2.49	-16.2%	**41.5%**	10.7%	26.6%
Area type (1=urban)	0.762	1.13	-10.4%	26.4%	17.7%	15.5%
Population density (per mi^2)	9.52E-05	**3.06**	-13.1%	**31.8%**	**35.1%**	17.8%
Retail employment density (per mi^2)	1.70E-04	1.20	-11.4%	27.9%	12.8%	14.4%

Service employment density (per mi^2)	-6.66E-05	**-3.10**	5.4%	-15.7%	-10.1%	-12.1%
Thresholds	**Coef.**	**Std. Dev.**				
Rely less than once a month **vs.** Rely at least once a month	-1.177	0.621	--	--	--	--
Rely at least once a month **vs.** Rely at least once a week	1.646	0.789	--	--	--	--
At least once a week **vs.** Rely entirely on SAV fleet	3.068	0.462	--	--	--	--
McFadden's R-Square: 0.171			**McFadden's adjusted R-Square:** 0.105			

Notes: N_{obs}=347. All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly statistically significant predictors. All ΔPr's with $|\Delta Pr_i|$ > 30% are in **bold,** and indicate practically significant predictors.

5.3 Willingness to Pay for CVs

Table 6 summarizes the OP model estimates of the WTP for CVs (i.e., not interested, neutral, or interested in adding connectivity to current vehicle at a cost of less than $100). These estimates indicate that respondents living farther from their workplace in higher household density urban neighborhoods, who carry a smart phone, and drive alone for work and social trips, ceteris paribus, are estimated to have greater interest in adding connectivity to their current vehicles. Perhaps the individuals who have higher annual VMT, have experienced more accidents, and have heard about Google's self-driving car, all other predictors remaining constant, are able to evaluate and appreciate the safety benefits of low-cost connectivity. Therefore, the corresponding predictors enjoy positive and practically significant relationships with WTP for CVs.

Table 6: Willingness to Pay for Connected Vehicles (Ordered Probit Model Results)

Covariates	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**
Have heard about Google car (1=yes)	1.196	2.15	**-32.4%**	-17.3%	21.1%
Number of past crash experiences	0.290	2.03	**-34.3%**	-19.2%	23.2%
Carry smartphone (1=yes)	1.026	1.88	-12.8%	-11.0%	10.2%
Drive alone for work trips (1=yes)	0.895	2.32	-13.1%	-16.3%	12.1%
Drive alone for social trips (1=yes)	0.627	1.44	-21.0%	-11.7%	12.9%
Annual VMT	5.77E-05	1.63	-22.7%	**-33.9%**	22.1%
Distance from workplace (miles)	0.057	1.71	-20.9%	-17.6%	16.3%
Area type (1=urban)	0.728	1.55	-20.3%	-15.4%	14.1%
Household density (per mi^2)	1.96E-04	1.88	-28.2%	-24.9%	21.5%
Thresholds	**Coef.**	**Std. Dev.**			
Not interested **vs.** Neutral	1.042	0.403	--	--	--
Neutral **vs.** interested	2.082	0.462	--	--	--
McFadden's R-Square: 0.127			**McFadden's adjusted R-Square:** 0.083		

Notes: N_{obs}=347. All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly statistically significant predictors. All ΔPr's with $|\Delta Pr_i|$ > 30% are in **bold,** and indicate practically significant predictors.

5.4 Adoption Timing of AVs

Table 7 summarizes the OP model estimates of the adoption timing of AVs (i.e., never adopt AVs, adopt AVs when 50% of friends adopt, when 10 % of friends adopt, or as soon as available in the market). AV adoption by older licensed drivers living farther from their workplace in high basic employment density neighborhoods, ceteris paribus, is more likely to depend on their friends’ adoption rates. However, males with higher household income, living in urban neighborhoods, and who travel more, all other attributes remaining constant, are estimated to have a practically significant inclination to adopt AVs, with less dependence on their friends’ adoption rates. Number of accidents experienced by the individual and the indicator variables, whether an individual has heard about Google’s self-driving car and if an individual thinks that ABS is a form of automation, exhibit a positive and practically significant association with AV adoption timing. This relationship indicates that techy-savvy individuals, who perceive the safety benefits of AVs, are more likely to adopt them with less dependence on their friends’ adoption rates.

Table 7: Adoption Timing of Autonomous Vehicles (Ordered Probit Model Results)

Covariates	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**	**ΔPr_4**
Have heard about Google car (1=yes)	1.523	**2.76**	**-34.5%**	-10.6%	-9.1%	**38.2%**
ABS form of automation (1=yes)	0.524	1.66	-24.1%	**-34.5%**	22.4%	27.9%
Number of past crash experiences	0.323	**2.60**	**-33.8%**	-22.1%	-15.8%	**51.9%**
Log(Annual VMT)	0.408	1.64	**-36.3%**	-24.1%	14.2%	**35.1%**
Distance from workplace (miles)	-0.043	-1.44	25.3%	19.4%	-12.3%	-21.6%
Gender (1=male)	0.603	1.98	**-37.1%**	-15.4%	19.1%	22.1%
U.S. driver license (1=yes)	-1.548	-1.57	20.7%	14.5%	-13.2%	-15.5%
Age	-0.013	-1.30	21.5%	29.8%	-22.3%	-21.7%
Annual household income ($ per year)	3.89E-06	1.92	-27.8%	**-35.9%**	**31.1%**	23.2%
Area type (1=urban)	0.798	2.21	-29.0%	-26.6%	11.1%	**32.8%**
Basic employment density (per mi^2)	-5.44E-04	**-3.41**	26.3%	19.0%	-7.3%	-25.4%
Thresholds	**Coef.**	**Std. Dev.**				
Never **vs.** 50% friends adopt	-5.765	0.794	--	--	--	--
50% friends adopt **vs.** 10% friends adopt	-4.241	0.271	--	--	--	--
10% friends adopt **vs.** **A**s soon as available	-2.973	0.780	--	--	--	--
McFadden’s R-Square: 0.097			**McFadden’s adjusted R-Square:** 0.066			

Notes: N_{obs}=347. “Log (Annual VMT)” was used as an explanatory variable in the model, but corresponding ΔPr’s were calculated with respect to “Annual VMT”. All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly statistically significant predictors. All ΔPr’s with $|\Delta Pr_i|$ > 30% are in **bold,** and indicate practically significant predictors.

5.5 Home Location Shifts due to AVs and SAVs

Table 8 summarizes the OP model estimates of respondents’ home-location-shift decisions (i.e., shift closer to central Austin, stay at the same location, or move farther from central Austin) after AVs and SAVs become common modes of transport. Results indicate that respondents with a greater number of children, living farther from their workplace in high employment density neighborhoods, and who drive alone for work trips, ceteris paribus, are predicted to shift farther from central Austin. Perhaps these individuals are excited about lower land prices in suburbs and are comfortable using their longer commute times pursuing other activities (e.g., working, talking with friends, and reading). People with Bachelor’s degrees, living in high household density neighborhoods, all other attributes remaining the same, also exhibit a practically significant inclination to shift farther from central Austin. Perhaps these individuals are concerned about higher land prices in the highly populated neighborhoods, and are keen to the benefits of moving to suburban areas after AVs and SAVs become common modes of transport. In contrast, full-time working males, with higher household income and higher VMT, all other predictors remaining constant, are likely to shift closer to central Austin, perhaps to appreciate and adopt low-cost SAVs' higher level of service. As expected, tech-savvy respondents (i.e., who carry a smartphone and are familiar with carsharing options), living in urban neighborhoods, ceteris paribus, are estimated to have a practically significant propensity to shift closer to central Austin.

Table 8: Home Location Shifts due to AVs and SAVs (Ordered Probit Model Results)

Covariates	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**
Carry smartphone (1=yes)	-0.926	-1.24	**45.8%**	-6.1%	-11.6%
Familiar with carsharing (1=yes)	-3.295	**-2.62**	**53.7%**	-8.5%	-15.3%
Drive alone for work trips (1=yes)	0.530	1.32	-27.7%	4.9%	8.7%
Annual VMT	-8.95E-05	**-2.61**	29.1%	-4.2%	-11.2%
Distance from workplace (miles)	0.044	1.14	-24.9%	2.9%	14.6%
Gender (1=male)	-0.882	**-2.71**	22.1%	-2.6%	-12.6%
Number of children	1.086	**3.27**	-17.2%	-1.3%	22.5%
Education level (1=bachelor's degree holder)	0.676	1.60	**-40.9%**	3.2%	**34.6%**
Annual household income ($ per year)	-3.40E-06	-1.49	19.2%	-1.9%	-14.1%
Employment status (1=full-time worker)	-0.636	-1.60	29.7%	-3.6%	-15.3%
Area type (1=urban)	-0.551	-1.08	**43.8%**	-6.9%	-10.2%
Household density (per mi^2)	3.43E-04	**3.35**	**-31.2%**	-2.8%	**48.9%**
Total employment density (per mi^2)	1.70E-05	1.19	-29.2%	3.5%	12.2%
Thresholds	**Coef.**	**Std. Dev.**			
Closer to central Austin **vs.** Stay at the same place	-6.408	1.235	--	--	--
Stay at the same place **vs.** Farther from central Austin	-1.034	2.345	--	--	--
McFadden's R-Square: 0.237			**McFadden's adjusted R-Square:** 0.156		

Notes: N_{obs}=347. All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly statistically significant predictors. All ΔPr's with $|\Delta Pr_i|$ > 30% are in **bold,** and indicate practically significant predictors.

6. CONCLUSIONS

Survey results offer many meaningful insights regarding Austinites' perceptions about CAV technology and related aspects. Average WTP for Level 4 AVs ($7,253) is much higher than that of Level 3 AVs ($3,300). More than 80% of respondents are interested in owning Level 4 AVs. For roughly 50% of the population, AV adoption rates appear to depend on adoption rates of friends and neighbors. And more than 80% appear unwilling to pay more for a SAV service than current carsharing and ridesharing companies are charging. More than 75% of respondents indicate interest in adding connectivity to their current vehicles, if the cost is under $100. Equipment or system failure appears to be the key concern with AV use, while learning how to use the smart vehicle is the least concerning. Respondents believe fewer crashes to be AVs' biggest or most likely benefit, and less congestion to be the least likely benefit. The top two activity picks, while riding in an AV, are looking out the window and talking with friends.

This study also estimated how respondent demographics, built-environment factors, and travel characteristics, impact their opinions about the benefits and concerns for, and adoption of CAVs. For example, regression-model based WTP estimates, SAV adoption rates (under different pricing scenarios), and AV adoption timing collectively suggest that high-income tech-savvy[13] males, living in urban areas and having greater crash experience have more interest in and a higher WTP for these new technologies, with less dependence on friends' adoption rates[14]. Perhaps such individuals are more able to appreciate and evaluate the safety benefits of smart technologies. Surveyed individuals also display a higher inclination to ultimately move closer to central Austin, possibly to enjoy the high-density of low-cost shared fleets (SAVs). In contrast, older licensed drivers expressed less interest in such technologies. They may concerned about having to learn how to use CAVs and SAVs, and licensed drivers may not be interested in losing the pleasure of driving entirely.

Individuals that drive more were found to be more likely to adopt AVs, with less dependence upon the adoption rates of friends, and willing to spend more to add Level 4 automation and connectivity, but expressed less interest in adding Level 3 automation or using SAVs costing $3 per mile. This result may be because those who travel longer distances by car can expect to benefit more from safer, more automated, and connected travel with Level 4 technology; and they can perform other activities en route (like work, reading, and talking with friends). This is not so feasible with Level 3 AVs, because drivers must be ready to take over the job of driving, rather quickly. Consistent with past carsharing studies (e.g., Celsor and Millard-Ball 2007), respondents living in denser neighborhoods were more interested in using SAVs under all three pricing scenarios offered here, perhaps due to inconvenient parking facilities and lower vehicle ownership rates in those locations.

This work's behavioral model parameter and results will be helpful to communities and nations in simulating long-term (e.g., year 2025 and 2040) adoption of CAV technologies, under different energy and vehicle pricing, demographic, and technology scenarios. These forecasted technology adoption rates can help urban planners to start organizing and zoning for development projects in housing, roadways, and complementary infrastructure. For example, if SAVs adoption is expected to take off in a couple of decades, there is a need to plan for parking lots, otherwise infrastructure may be locked-in and might raise future costs in accommodating SAVs. Such results will hopefully usher in smarter, safer, connected, and more sustainable ground transportation systems.

As suggested by this work, individuals foresee substantial benefits of CAVs, but also perceive hurdles. If such hurdles, or potential barriers, are not understood and managed thoughtfully, they can slow AV adoption rates to socially sub-optimal levels. Armed with such information, public agencies can craft specific policies. For example, they may create opportunities for citizens to "observe" and then "try" CVs, AVs, and CAVs, in experience and better evaluate the "relative advantages" of such technologies. Such experiences are essential ingredients for widespread and rapid technology diffusion (Rogers 2003).Anticipating sizable profit implications, businesses

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[13] A technology-savvy individual is one who has at least one of these attributes: has heard of Google's self-driving car, thinks that ABS is a form of automation, carries smart phone, or is familiar with local carsharing and ridesharing companies.

[14] Most of the related covariates are statistically significant and many of these are practically significant in the models for WTP for AVs, adoption rates of SAVs, WTP for CVs, and adoption timing of AVs. Some of them could not achieve threshold |Z-value| (1.0) for statistical significance, and therefore, are not included in the tables exhibiting the models' results.

also an interests in creating (and, in some cases, slowing) such opportunities. Key demographic factors and built-environment settings identified here can help businesses and public agencies to target groups with lower expected WTP values, for large-scale, real-world pilots and thoughtful design of more successful public-private partnerships.

We live in a very early stage for public engagement with and understanding of CAVs and SAVs. As communities and individuals learn more about these emerging vehicle-based technologies, their perceptions and expected/stated behavioral responses are likely to change, in some cases rapidly. As such, more such work is required elsewhere in the U.S. and other countries, and over time. Our world is at dynamic stage, facing an important and impending transition in transportation. Knowledge of underlying factors across geographies and over time will be important in helping all relevant stakeholders – public, businesses, regulators, and policymakers – coordinate to enable an effective and efficient transformation of the transportation system.

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