ARE WE READY TO EMBRACE CONNECTED AND SELF-DRIVING VEHICLES? A CASE STUDY OF TEXANS

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

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ABSTRACT

While connected, highly automated, and autonomous vehicles (CAVs) will eventually hit the roads, their success and market penetration rates depend largely on public opinions regarding benefits, concerns, and adoption of these technologies. Additionally, these technologies bring many future uncertainties in carsharing market and land use patterns, and also raises need for tolling policies to appease the travel demand induced due to the convenience brought by them. To these ends, this study surveyed 1,088 respondents across Texas to understand their opinion about smart vehicle technologies and related decisions. The key summary statistics indicate that Texans are willing to pay (WTP) \$2,910, \$4,607, \$7,589, and \$127 for Level 2, Level 3, and Level 4 automation and connectivity, respectively, on average. Moreover, affordability and equipment failure are Texans' top two concerns regarding AVs.

This study also estimates interval regression and ordered probit models to understand the multivariate correlation between explanatory variables such as demographics, built-environment attributes, travel patterns, and crash-history, and response variables including willingness to pay for CAV technologies, adoption rates of shared autonomous vehicles at different pricing points, home location shift decisions, adoption timing of automation technologies, and opinion about various tolling policies. The practically significant relationships indicate that more experienced licensed drivers have higher WTP for connectivity, but older people associate lower values with all automation technologies. Such parameter estimates not only help in forecasting long-term adoption of CAV technologies, but also help transportation planners in understanding the characteristics of regions with high or low future CAV technologies' adoption, and subsequently, develop smart strategies in respective regions.

Key words: connected and autonomous vehicles; ordered probit; interval regression; public opinion survey; willingness to pay.

Highlights

- We survey and outline Texans' opinions on connected and autonomous vehicles (CAVs).
- We estimate their willingness to pay (WTP) for CAVs technologies.
- Their average WTP for Level 3 and Level 4 automation is \$4,607 and \$7,589.
- 81.5% Texans' do not plan to shift their home locations in CAV paradigm.
- Older people associate lower values with all automation technologies.

INTRODUCTION AND MOTIVATION

Automated and (fully) autonomous vehicles (AVs), connected vehicles (CVs), and connected autonomous vehicles (CAVs) are the most significant technological advances of the century in our transportation systems. CAVs have the potential to dramatically reduce 90% of all crashes that result from driver error (NHTSA 2008). However, convenience brought by these technologies is likely to induce demand for travel, so overall safety impacts remain questionable (Anderson et al. 2014). Roadways operators may need to adopt smart congestion-pricing strategies (like credit-based pricing or other distributions of toll revenues) in order to keep traffic moving in high-demand corridors and maximize public benefits.

Many recent studies have expressed excitement about shared AVs (SAVs) as a new mode of transport (Burns et al. 2013, Fagnant et al. 2015). Such on-demand "autonomous taxis" enable short-term rental while lowering AV access issues and costs (Fagnant and Kockelman 2014). The higher density of low-cost SAVs in the city center can motivate people to move near city center in the future and at the same time, convenience to utilize travel time while riding AVs may encourage them to live in suburbs to enjoy lower land prices. Thus, the future land use pattern is likely to depend on the public's polarization toward different conveniences and this raises crucial policy questions about regularization of land prices and SAV's costs.

Thus, the complexity and ambiguity of the transportation future that CAV technologies are about to bring is overwhelming. The public is going to be the main force in determining how this future will evolve. Many researchers (e.g., Bansal et al. 2015, Casley et al. 2013, Howard and Dai 2013, Schoettle and Sivak 2015, Kyriakidis et al. 2015), private firms (Cisco Systems 2013, Ipsos MORI 2014, J.D. Power 2015, KPMG 2013), and others, such as NerdWallet (Danise 2015), Open Roboethics initiative (2014), and Insurance.com (Vallet 2014), have conducted public opinion surveys regarding AVs. They have concluded that the public is still very cautious about the concept of driverless vehicles and that many people are concerned about the price, safety, and security of AVs. However, to the best of our knowledge, only Bansal et al.'s (2015) work has gone beyond pairwise correlation analysis to uncover connections between responses and various factors.

Similar to Bansal et al.'s (2015) study of 347 respondents from Austin (Texas' capital city), this study estimates econometric models to understand multivariate relationships between Texans' opinions of CAV technologies and their demographic characteristics and built-environment factors on the larger sample of 1,088 respondents, and with additional explanatory variables (e.g., crash history and opinion about safety regulations). Revealing these relations provides understanding of the main determinants that make individuals favor or despise these technologies, or impact their decisions to support related policies. This knowledge provides

insights about the potential demand for CAVs, allows forecasting AV fleet evolution (as illustrated by Bansal and Kockelman [2015]), and helps policymakers and public officials in making decisions about infrastructure evolution, handling legal and safety issues, and various other aspects of the connected and autonomous system.

To this end, a Texas-wide survey was conducted, asking questions about benefits of and concerns of CAVs, crash history, opinions about speed regulations, WTP for and interest in CAV technologies, demographics, travel patterns, among many others. The results reveal general understanding of the public's current stands on the questions about WTP for CAV technologies, perception about the important benefits and key issues, adoption rates of SAVs at different pricing points, home location shift decisions (once AVs and SAVs become common modes of transportation), adoption timing of and WTP for CAV technologies, and opinion about tolling policies to curve the demand induced by the convenience brought on by these technologies. The following sections describe related studies, the survey design, summary statistics, estimation methods, key findings, and conclusions.

LITERATURE REVIEW

Academic and professional researchers, private enterprises, and auto-related websites conducted surveys to understand public opinions about CAV technologies and related aspects. Most of the surveys demonstrate that the public is still very cautious about these technologies and potential of driverless vehicles, often citing safety, affordability, and information security as their main concerns.

Among the academic and professional research, Casley et al. (2013) conducted a survey of over 450 participants in university setting. They found that respondents ranked safety as their biggest concern, and legislation problems as the second biggest concern in using AVs. They also discovered that most respondents believed that the self-driving feature will cost about \$5,000 (in addition to the vehicle price), while most of the respondents were only willing to pay about \$1,000 for it. Schoettle and Sivak conducted several surveys of public opinion regarding CAVs. The newest one Schoettle and Sivak (2015) yielded 505 complete responses from motorists in the U.S. It revealed that non-autonomous is the most preferred mode of transportation for motorist (43.8%), followed by partial-autonomous (40.6%), with full-autonomous being the least preferred option (15.6%). Young motorists and men were more inclined to prefer partial or full automation over no automation, while women and older people generally voted for no automation. Bansal and Kockelman (2015) surveyed 2,167 Americans to understand their opinions about and adoption of CAV technologies. They found that average WTP to add connectivity and Level 4 automation were \$67 and \$5,857, respectively. Approximately half of the respondents were comfortable in sharing their vehicle information to other vehicles, but this fraction reduced to 40% when it came to vehicle manufactures. Additionally, approximately 40% of respondents showed interest in using AVs for long distance trips (one way distance greater than 50 miles). In another study, Bansal et al. (2015) surveyed 347 Austinites to understand their opinions about CAV technologies and related aspects. They found that equipment failure was the main concern of Austinites, but learning to use AVs was the least. Underwood (2014) surveyed

¹ NHTSA (2013) defined different vehicle automation levels. Succinctly, "automation Levels 0, Level 1, Level 2, Level 3, and Level 4 imply no automation, function-specific automation, combined function automation, limited self-driving automation, and full self-driving automation, respectively."

industry experts and professionals. According to the results of the survey, legal issues and technological limitations were most often chosen as the main barriers for full-autonomous vehicles. Surprisingly, infrastructure adjustment was chosen as the least important barrier. More than one-quarter of experts agreed that AVs must be at least twice as safe as conventional vehicles to be authorized for public use. More than three-quarters believe it will be socially acceptable for AVs to cause fatal crashes from time to time. Howard and Dai (2013) surveyed 107 visitors of Lawrence Hall of Science in Berkeley, California. They found that safety was the most attractive feature of AVs for visitors, while control was the least attractive feature. Approximately the same number of respondents (about 40%) replied that they would retrofit their current car with a self-driving technology and that they would buy a new self-driving car. In Europe, Kyriakidis et al. (2015) studied more than 5000 responses to a survey asking questions about acceptance of, concerns associated with, and willingness to pay for various vehicle automation technologies. They discovered that respondents from all over the world were most concerned about information security issues (e.g., hacking attacks) and legal liability associated with operating an AV. Approximately 22% of respondents did not want to pay any additional money to add full automation to their vehicle and only 5% were willing to pay more than \$30,000.

Private firms conducted extensive studies about public perception of AVs. Accenture Research (Vujanic and Unkefer 2011) found that 49% of the respondents in the U.S. and in the U.K. would be comfortable using a driverless electric vehicle. Among those who would not be comfortable, 48% indicated that they would be encouraged to use these vehicles if it was possible to regain control if needed. Recently J.D. Power (2015) surveyed more than 5,300 new-car-buyers to understand their vehicle technology preferences. They found that younger generations (generations X and Y) have higher preferences for advanced automation technologies than Boomers and Pre-boomers who, in contrast, were more inclined towards Level 1 automation technologies. Blind-spot monitoring and night vision were the most preferred technologies across all respondents. A new study published by a German firm, Puls Marktforschung (2015), indicated that among more than 1,000 respondents, 32.4% expressed positive opinions towards the new developments in vehicle automation technologies. When answering questions about changes that AVs can bring, 50.2% agreed that AVs will improve mobility of those who cannot drive, and 40% indicated that AVs will help in reducing road congestion. In a worldwide industry study, Cisco Systems (2013) analysts revealed that 57% of respondents trust driverless cars, with developing countries' citizens expressing higher trust than respondents from already developed countries. Golman Sachs analysts (Yuzawa et al. 2015) published results of a survey conducted in Europe by Motor Fan. The survey indicates that 60% of respondents think that AVs allowing drivers to interfere (Level 3 automation) is a good idea; however, only 44% think that AVs will be safer than conventional vehicles. A British firm, Ipsos Mori (2014), asked 1,001 Britons about their opinions about AVs. The replies were not surprising: only 18% of respondents thought it is important for car manufacturers to focus on driverless technologies; more men and younger people indicated these technologies to be important than women or older Britons. A survey of respondents from China, Germany, Japan, and U.S.A. by Continental (Sommer 2013) uncovered that 79% respondents in China perceive automated driving as useful advancement, while only 41% of the respondents in the U.S. felt the same. However, 74% of respondents from China did not believe AVs will function reliably, and only 50% of respondents in the U.S. agreed. Most of the respondents indicated they would feel comfortable riding in AVs in light traffic and on long freeway journeys. KPMG (2013) conducted three focus groups in the

U.S. to elicit opinions about AVs. They discovered that technology companies and premium auto brands are top preferences for the manufacturers of AVs. Women were slightly more receptive to the concept of an AV than men. The median premium amount that consumers were willing to pay to add self-driving capability to a \$30,000 car was \$4,500.

Several websites conducted and published results based on polls of their visitors. An online study conducted by Insurance.com (Vallet 2014) concluded that about 22.4% of the respondents are ready to ride in a Level 4 AV, while in contrast, 24.5% replied they will never use AVs. However, a possible 80% discount on car insurance changed these numbers to 37.6% and to 13.7%, respectively. This result suggests that monetary considerations significantly affect perceptions of AV technology. Website Open Roboethics initiative (2014) conducted several surveys online. Some of the results demonstrate that about half of the respondents will miss the joy of driving a car. Among these, about 45% will miss having full control over the car. Reduction of crashes and utilization of travel time were ranked as the key benefits of AVs. About two-thirds indicated they will pay more than \$3,000 in addition to the price of the conventional vehicle to have full automation. Website NerdWallet (Danise 2015) performed a short survey and found that women were less interested than men in owning a self-driving car and that only 3% were planning to buy driverless cars as soon as they become available. Affordability and safety were cited as top issues associated with driverless cars by women, while men indicated affordability and lack of driving fun as their main concerns.

This research builds on the existing opinion-based studies and provides new insights about various related aspects not covered by most of these studies, such as home location decisions and adoption rates of SAVs under different pricing scenarios, among many others. Additionally, ordered probit (OP) and interval regression (IR) models were estimated to understand multivariate relationship between response variables and Texans' demographic and built-environment characteristics.

SURVEY DESIGN, DATA CLEANING, AND GEOCODING

A Texas-wide survey, asking 93 questions distributed in 7 sections, was disseminated through Survey Sampling International's (SSI, a professional survey firm) continuous panel in June-July 2015 using Qualtrics, a web-based survey tool. Respondents were asked about their opinions regarding AVs (e.g., concerns and benefits of AVs), crash history and opinions about speed regulations² (e.g., number of moving violations, and support for red light cameras and automated speed enforcement), WTP for and interest in various Level 1 and 2 technologies (e.g., adaptive headlights and adaptive cruise control). Respondents were also asked about their WTP for and interest in CVs (e.g., road sign information using a head-up display), adoption rates of carsharing, Transportation Network Companies' (TNC's) services, and SAVs, their households' home-location shifting decisions (once AVs and SAVs become common modes of transport), opinions about congestion pricing strategies (e.g., toll if revenue is evenly distributed among residents), travel patterns (e.g., AVs' usage by trip purpose and distance from city's downtown), and demographics.

² Respondents' crash history and opinions about speed law enforcement were asked to explore correlation of such attributes with their opinions of and WTP for CAV technologies.

A total of 1,297 Texans completed the survey, but after eliminating the fast responses and going through various sanity checks³, 1,088 Texans remained eligible for further analysis. Since, sample over-represented and under-represented various demographic groups, person- and household- level weights were calculated to un-bias the summary statistics and model parameter estimates for person-based (e.g., key concern about AVs) and household-based responses (e.g., home location shift decision), respectively. To calculate person-level weights, the survey sample proportions in three demographic classes or sixty categories (two gender-based, five age-based, and six educational-attainment groups) were scaled using the 2013 American Community Survey's PUMS for Texas⁴, and household-level weights were calculated for 3 demographic classes or 26 categories (4 household size groups, 4 household workers groups, and 2 vehicle ownership groups)⁵.

To understand the relationship between built-environment factors (e.g., population density and proportion of population below poverty line) and Texans' opinions about CAV technologies, geographic locations (latitudes and longitudes) of the respondents' homes were obtained using Google Maps API and these locations were mapped with open-source census-tract-level shape file in ArcGIS. The internet protocol (IP) locations were used as proxies for the respondents who recorded wrong or no street address. Figure 1 shows the geocoded respondents across Texas, with most respondents living in or around Texas' biggest cities (Houston, Dallas, Fort Worth, San Antonio, and Austin), as expected in a relatively unbiased sample.

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³ Respondents who completed the survey in less than 15 minutes were assumed to have not read questions thoroughly, and their responses were discarded. Respondents were provided with NHTSA's automation levels' definitions and, subsequently, were asked whether they understood this description or not. Those who did not understand it (5.7%, or 65 respondents) were considered ineligible for further analysis. Certain other respondents were also considered ineligible for further analysis: those younger than 18 years of age, reporting more workers or children than the household size, reporting the same distance of their home from various places (airport and city center, for example), and providing other combinations of conflicting answers.

⁴ The categories of "Master's degree holder female and 18 to 24 years old" and "Master's degree holder male and 18 to 24 years old" were missing in the sample data. Thus, these population categories were merged with "Bachelor's degree holder female and 18 to 24 years old," respectively, to create population correction weights.

⁵ There are 32 combinations of traits ($4 \times 4 \times 2 = 32$), but there are only 26 categories because some of the categories cannot exist. For example, the number of workers cannot exceed household size. A category "household with more than three members, more than two workers, and no vehicle" was missing and was merged with "household with more than three members, two workers, and no vehicle" in the population.

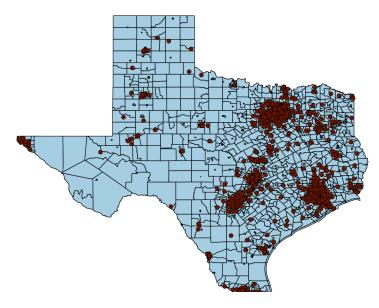


Figure 1: Geocoded Respondents across Texas

SUMMARY STATISTICS

Table 1 summarizes all explanatory variables used in several model calibrations of this study. These are grouped into six categories, based on these predictors: person, household, location, travel, technology, and safety. Person- and household-based weights, as appropriate, were employed in calculating summary statistics and model calibration to correct for sample biases.

Texans' Technology-awareness and Safety-related Opinions

Technology-based predictors provide key insights about Texans' attitude towards new technologies. Approximately 77% of (population-weighted) Texans use a smartphone and slightly more than a half (59%) know about the existence of Google self-driving cars; however, only 19% have ever heard about CVs (before participating in the survey). Surprisingly, around two-thirds are familiar with TNC's services like UberX and Lyft, but only 25% are aware about the carsharing programs. Only 7% of respondents' households own at least a modern vehicle with Level 2 automation.

Texans' attitudes towards safety-regulation strategies, crash history, and moving violation history are captured in the safety-based predictors. Around half of the respondents support each of these speed regulation strategies: red light cameras, automated speed enforcement, and speed governors. On average, Texans have experienced 0.25 crashes involving fatalities or serious injuries and 0.7 crashes involving monetary losses in past 15 years. Each respondent received at least one moving violation within past ten years, on average, while 20% received more than one violation. As per these statistics, Texans appear to be average drivers in terms of safety precautions.

Table 1: Population-weighted Summary Statistics of Explanatory Variables (Nobs=1,088)

Type	Explanatory Variable	Mean	SD	Min.	Max.
on- ed lict	Licensed driver (number of years)	19.11	12.50	0	32.5
Se se	Licensed driver for more than 20 years	0.51	0.50	0	1
Per ba	Have U.S. driver license?	0.86	0.35	0	1

Type	Explanatory Variable	Mean	SD	Min.	Max.
	Age of respondent (years)	44.56	16.31	21	69.5
	Younger than 34 years?	0.34	0.47	0	1
	Older than 54 years?	0.33	0.47	0	1
	Ethnicity: White, European white or Caucasian?	0.59	0.49	0	1
	Marital Status: Single?	0.33	0.47	0	1
	Marital Status: Married?	0.49	0.50	0	1
	Gender: Male?	0.49	0.50	0	1
	No disability?	0.90	0.09	0	1
	Bachelor's degree holder?	0.25	0.43	0	1
	Employment: Unemployed?	0.22	0.42	0	1
	Employment: Full time worker?	0.34	0.47	0	1
	Household size over 3?	0.27	0.45	0	1
ed	Household income (\$)	59,506	46,843	5,000	225,000
bas irs	Household income is less than \$30,000?	0.28	0.45	0	1
Household-based Predictors	Household size	2.62	1.43	1	9
sho edi	Number of workers in household	1.21	0.89	0	6
use Pr	More than one worker in household?	0.36	0.48	0	1
$_{ m H_0}$	Own at least one vehicle?	0.94	0.24	0	1
	Number of children in household	0.62	1.05	0	6
	Distance between home and public transit stop (miles)	6.12	6.20	0.5	17.5
s	Distance between home and city's downtown (miles)	9.59	5.97	0.5	17.5
-ba tor	Home and city's downtown are more than 10 miles	0.47	0.50	0	1
ion dic	Distance from city center (miles)	9.85	7.46	0.5	25
Location-based Predictors	Employed and over 16 years of age (per square mile)	2,536	2,619	0	20,384
Lo	% of families below poverty line in the census tract	13.01	11.20	0	100
	Population density (per square mile)	3,253	3,366	1	32,880
	Drive alone for work trips?	0.51	0.50	0	1
s. seq	Number of personal business trips in past 7 days	1.58	2.26	0	9.5
bas tor	More than 2 personal business trips in past 7 days?	0.20	0.40	0	1
Travel-based Predictors	Number of social (or recreational) trips in past 7 days	2.25	2.23	0	9.5
rav Pre	More than 2 social (or recreational) trips in past 7 days?	0.31	0.46	0	1
Ē	Annual VMT (miles)	8,607	6,391	1,500	22,500
	Annual VMT is more than 15,000 miles?	0.17	0.38	0	1
_	Carry a smartphone?	0.77	0.42	0	1
sec	Have heard about Google car?	0.59	0.49	0	1
Fech-based Predictors	Familiar with UberX or Lyft?	0.64	0.48	0	1
ch red	Have heard about CVs?	0.19	0.15	0	1
Te Pı	Familiar with carsharing?	0.25	0.44	0	1
	Own at least a vehicle with Level 2 automation?	0.07	0.26	0	1
	Support the use of Red Light Camera?	0.54	0.50	0	1
p	Support the use of Automated Speed Enforcement?	0.52	0.50	0	1
Safety-based Predictors	Support the use of Speed Governors on all new	0.48	0.50	0	1
y-b. lict	Number of fatal (or serious) crashes in past 15 years	0.28	1.43	0	16
fet, red	At least one fatal (or serious) crash in past 15 years	0.08	0.27	0	1
Sa	Number of crashes with only monetary loss in past 15	0.70	1.87	0	18
	Number of moving violations in past 10 years	0.97	2.23	0	26
	More than one moving violation in past 10 years?	0.20	0.40	0	1

Key Response Variables

Table 2 shows respondents' opinions about and average WTP for different automation levels and connectivity⁶. Texans valued Level 2, Level 3, and Level 4 automation at \$2,910, \$4,607, and \$7,589, on average; in contrast, 54.4%, 31.7%, and 26.6% of Texans are not willing to pay more than \$1,500 for these technologies, respectively. As expected, the average WTP increases with level of automation. Interestingly, around half of Texans' (47%) will likely time their AV adoption in conjunction with their friends' adoption rates⁷.

Texans are willing to spend \$127, on average, for connectivity, but 29.3% of the respondents are not willing to spend any money at all to add it, and only 39% are interested even if it is affordable. Thus, NHTSA's probable regulation on mandatory adoption of connectivity in all new vehicles from 2020 can play a key role in boosting CV adoption rates (Automotive Digest 2014).

Table 2: WTP for and Opinions about Connectivity $(1,063)^8$ and Automation Technologies $(N_{obs}=755)^9$

Response Variable	Percentages	Mean	SD	Min.	Max.
WTP for Adding Connectivity		\$127	\$164	\$0	\$1,100
\$0	29.3%				
\$1 to \$99	28.1%				
\$100 to \$199	20.4%	1			
\$200 to \$299	11.2%	1			
\$300 or more	11.0%	1			
WTP for Adding LV 4 Automation		\$7,589	\$7,628	\$750	\$31,500
Less than \$1,500	26.6%				
\$1,500 to \$5,999	28.7%				
\$6,000 to \$11,999	13.6%	1			
\$12,000 or more	31.1%	1			
WTP for Adding LV 3 Automation		\$4,607	\$5,421	\$750	\$31,500
Less than \$1,500	31.7%				
\$1,500 to \$2,999	24.5%	1			
\$3,000 to \$5,999	21.4%	1			
\$6,000 or more	22.4%	1			
WTP for Adding LV2 Automation		\$2,910	\$4,312	\$750	\$31,500
Less than \$1,500	54.4%				
\$1,500 to \$2,999	23.3%]			
\$3,000 or more	22.3%]			
Adoption timing of Level 4 AVs		Response Var	iable		Percentages

⁶ Respondents were informed that connectivity can be added to an existing vehicle using a smartphone and some additional equipment with dedicated short-range communications (DSRC) technology and inertial sensors. This feature can be used to send alerts to the driver in form of audible sounds (like a message to "slow down" when congestion is forming up ahead or the roadway is deemed slippery) or in text format (like real-time travel times to one's destination).

⁷ Another interesting opinion summary indicates that most Texans (80%) are not ready to send their children alone in self-driving vehicles and around the same proportion of respondents (78%) are not in support of banning conventional vehicles when 50% of all new vehicles are self-driving.

⁸ The questions about interest in and WTP for connectivity were only asked to those (1,063 out of 1,088 respondents) whose households have a vehicle or are planning to buy a vehicle in the next 5 years.

⁹ The questions about WTP for different automation levels were asked only of those (755 out of 1,088 respondents) who are planning to buy a vehicle in the next 5 years.

Response Variable	Percentages	Mean	SD	Min	Max.	
Never	39%	Interest in adding connectivity				
When 50% friends adopt	32%	Not interes	ted		26%	
When 10% friends adopt	15%	Neutral		Neutral		35%
As soon as available	14%	Interested			39%	

Note: All paper results are population weighted/sample corrected.

Table 3 shows respondents' opinions about SAV adoption in different pricing scenarios and home-location shifting decisions when AVs and SAVs become common modes of transport. Around 41% of Texans feel that they are not yet ready to use SAVs (if such vehicles existed today), and only 7.3% presently hope to rely entirely on an SAV fleet, even at just \$1-per-mile pricing. Availability of AVs and SAVs does not appear to affect most Texans' decisions about moving closer to or farther from the city center: about 81.5% indicated their intention to stay at their current locations. This finding is consistent with Bansal et al.'s (2015) Austin study, where 74% of Austinites expect to remain at their current home locations. It is interesting that Texans' support for different congestion pricing policies do not vary much, on average. However, among the three congestion-pricing policies offered, most Texans (37.3%) support such highway tolls if the resulting revenues are used to lower property taxes.

Table 3: Opinions about SAV Adoption Rates, Congestion Pricing, and Home Location Shifting $(N_{obs}=1,088)$

	(1 1008	-1,000)		
Response Variable	Percentages	Response Variable	Percentages	
Adoption Rates of SAVs at \$1/m	ile	Adoption Rates of SAVs at \$2/mile		
Will Not Use	41.0%	Will Not Use	48.6%	
Less Than Once a Month	17.5%	Less Than Once a Month	19.8%	
Once a Month	17.5%	Once a Month	15.4%	
Once a Week	16.7%	Once a Week	11.6%	
Rely Entirely	7.3%	Rely Entirely	4.6%	
Adoption Rates of SAVs at \$3/m	ile	Home Location Shift due to AVs &	SAVs	
Will Not Use	59.1%	Move closer to city center	7.4%	
Less Than Once a Month	17.2%	Stay at the same location	81.5%	
Once a Month	11.7%	Move farther from city center	11.1%	
Once a Week	8.1%			
Rely Entirely	3.9%			
Toll Congested Highways if Rea	luce Property Tax	Toll Congested Highways if Distrib	oute Revenues	
Definitely not support	25.1%	Definitely not support	26.6%	
Probably not support	11.5%	Probably not support	14.2%	
Do not know	26.2%	Do not know	26.3%	
Probably support	22.6%	Probably support	21.4%	
Definitely support	14.7%	Definitely support	11.5%	
Time-varying Tolls on All Cong	ested Roadways			
Definitely not support	22.8%			
Probably not support	11.3%			
Do not know	31.8%	7		
Probably support	24.6%	7		
Definitely support	9.5%			

Note: All paper results are population weighted/sample corrected.

Opinions about AVs and CVs

Table 4 suggests that only 28.5% of Texans are not interested in owning or leasing Level 4 AVs (if affordable), indicating that they are excited about self-driving cars. Respondents were asked about the activities they believe they will perform while riding in a self-driving vehicle; talking to other passengers (59.5%) and looking out the window (59.4%) were two most popular responses¹⁰. Among those Texans who are interested in AVs, most would let their vehicle drive itself on freeways (60.9%) and in scenic areas (58.6%), but they are least comfortable riding in AVs on congested streets (36.1%). Among those who indicated interest in using self-driving vehicles, 33.9% are interested in using AVs for all trip types and 24.7% indicated interest in using AVs for social or recreational trips.

Table 4: Opinions about Level 4 Self-driving Technology (Nobs=1,088)

Response Variable	riable Percentage Response Variable		Percentage
Interest in Level 4 AVs (if affordable)			
Not Interested	28.5%	Moderately Interested	28.6%
Slightly Interested	21.0%	Very Interested	21.9%
Activities to be Performed while Riding is	n Level 4 AVs		
Watch movies or play games	27.3%	Sleep	18.1%
Surf the internet	33.3%	Look out the window	59.4%
Text, or talk on phone	46.2%	Exercise	7.8%
Talk to others in a car	59.5%	Maintenance activities	17.5%
Eat or drink	56.0%	Work	17.4%
Read	24.5%		
Like to Ride in AVs on $(N_{obs} = 863)^{11}$			
Freeway	60.9%	Scenic Areas	58.6%
Less congested streets	51.0%	Parking	43.6%
Congested streets	36.1%	Other	8.1%
Set Self-drive Mode During ($N_{obs} = 863$)			
All types of trips	33.9%	Personal business trip	17.0%
Work trip	17.0%	Recreational trip	24.7%
School trip	7.0%	Shopping trip	17.9%

Note: All paper results are population weighted/sample corrected.

Table 5 summarizes key concerns and benefits of AVs. Affordability and equipment failure are the top two concerns regarding AVs; the two least concerning aspects are learning how to use AVs and, surprisingly, privacy breaches. Texans expect that AVs can help attain better fuel economy and also reduce crashes: 53.9% and 53.1% of the respondents, respectively, indicated that these benefits will be very significant.

Table 5: Major Concerns and Benefits Associated with AVs (N_{obs}=1,088)

Major Concerns Associated with Self Driving	Not Worried	Slightly Worried	Very Worried
Equipment failure	8.4%	30.2%	61.4%
Legal liability	14.2%	32.8%	52.9%
Hacking of vehicle	15.1%	29.9%	55.1%

¹⁰Around 45% of Texans eat or drink at least once a week while driving, and this proportion is expected to increase to 56% while riding in self-driving vehicles.

¹¹ The respondents who intend to never ride in AVs were not asked about their AV usage preferences based on trip type or road characteristics.

Privacy breach	26.3%	39.0%	34.7%
Interactions with conventional vehicles	11.7%	34.5%	53.8%
Learning to use AVs	37.6%	37.7%	24.7%
Affordability	9.1%	26.4%	64.5%
Major Benefits from AVs	Insignificant	Slightly	Very Significant
Fewer crashes	7.3%	39.6%	53.1%
	1.570	39.0%	33.170
Less congestion	10.8%	44.6%	44.6%

Note: All paper results are population weighted/sample corrected.

Table 6 demonstrates Texans' current usage and interest in certain connectivity features as well as support for connectivity-based strategies. Automated notification of emergency services in an event of an accident and vehicle health reporting are the two connectivity features of greatest interests to Texans: with 71.5% and 68.5% of respondents reporting interest, respectively. Invehicle displays allowing one to compose emails and surf the Internet are the two least interesting features: 58.1% and 51.5% of the respondents indicated no interest in these features. And most features offered in the survey come with lower than 10% adoption rates. Real-time traffic information and operating a smartphone using controls on a steering wheel are the two most adopted features, with current adoption rates of 15.6% and 13.4%. Additionally, Texans appear likely to support adaptive traffic signal timing and but unlikely to support real-time adjustment in parking prices (when 80% of vehicles are connected): 64.0% and 20.5% of respondents reported support for these policies, respectively. On average, Texans ranked safety

as the most important and climate change as the least important area of improvement in automobile technologies.

Table 6: Current Adoption and Opinion about Connectivity Features and Strategies

Adoption of Connectivity Feature (Nobs=1,063) 12	Not Interested	Interested	Alread y Using
Real-time traffic information	22.6%	61.8%	15.6%
Alert about the presence of roadside speed cameras	27.6%	65.6%	6.7%
Information about nearby available parking	33.6%	61.7%	4.7%
Automatic notification to emergency personnel in case of	18.8%	71.5%	9.7%
Automatic monitoring of driving habits by insurance companies	49.6%	44.2%	6.2%
Personal restrictions (example: certain speed limits for teenagers)	38.4%	53.8%	7.8%
Alcohol detection	38.0%	53.8%	8.2%
Road sign information	37.4%	58.1%	4.5%
Cabin pre-conditioning	27.3%	65.6%	7.1%
Vehicle health report	19.3%	68.5%	12.2%
Vehicle life-cycle management	23.2%	63.5%	13.3%
Surfing the Internet via a built-in car display	51.5%	43.2%	5.2%
In-vehicle feature allowing to use email	58.1%	38.3%	3.6%
Operating a smartphone using controls on the steering wheel	38.5%	48.1%	13.4%
Connectivity-based strategies (N _{obs} =1,088)	Do Not Support	No Opinion	Suppor t
Adaptive traffic signal timing to ease congestion	13.0%	23.1%	64.0%
Real-time adjustment of parking prices	48.5%	31.0%	20.5%
Variable toll rates on congested corridors	37.3%	29.2%	33.5%
Variable speed limits based on road and weather conditions	18.3%	19.5%	62.2%
Areas of Improvement (Nobs=1,088)	Average Rank		
Safety	1.36		
Emissions (excluding greenhouse gas)	2.27		
Travel times (and congestion)		2.64	

Note: All paper results are population weighted/sample corrected. Top two values in each column are in **bold**.

Opinions about Carsharing and Transportation Network Companies (TNCs)

Table 7 shows that, among those who have heard about carsharing, only 10% are members of carsharing programs (e.g., Zipcar or Car2Go). These members indicated that environmental friendliness and monetary savings are the two key reasons behind joining the programs. Among non-member respondents, most (75.5%) find no current reason to join a carsharing program because they rely on other means of transportation. Among those who have heard about UberX or Lyft, only 12.2% have used such services as a passenger. According to these users, cost and time savings are their primary reasons for using such services. Lastly, only 16.4% of Texans report being comfortable in sharing a ride with a complete stranger.

Table 7: Opinions about Carsharing and On-demand Taxi Services (N_{obs}=1,088)

_	<u> </u>	, , ,
Carsharing (Zipcar, Gar2Go)		
Heard about carsharing	25.5%	
Among those who have heard about carshari	ing:	

¹² Questions about interest in connectivity features were asked only of those (1,063 out of 1,088 respondents) whose households have a vehicle or are planning to buy a vehicle in the next 5 years.

Member of Zipcar or Car2Go	9.9%	9.9% Not a member 90.1		
Why a member? (Among members)		Why not a member? (Among non-members)		
Saves money	68.2%	Not available where I live	25.9%	
Saves time	60.0%	Inconvenient availability or location	21.6%	
Environmentally friendly	68.7%	Own a vehicle, use transit, or walk	75.5%	
Necessity (I have no car)	38.6%	It is expensive	10.3%	
Good back up	35.9%	Not ready to share a vehicle	27.6%	
Other	5.2%	Other	18.2%	
On-demand Taxi Service (UberX or Ly	/ft)		•	
Heard about UberX or Lyft 64.0%				
Among those who heard about UberX or	Lyft:			
Used UberX as a Passenger		12.2%		
With Whom Will be Comfortable Sha	aring a Ride			
With a stranger	16.4%	With close friends and family	75.9%	
With a friend of a friend	39.9%	Other	2.6%	
With regular friends and family	45.4%			
Among those who Have Used UberX as P	Passengers		•	
Why Used UberX	•			
To save money	54.4%	No need to worry about parking	21.4%	
To save time	47.0%	My vehicle was unavailable	16.9%	
To try it out	43.3%	Promotion	24.1%	
To avoid driving	41.6%	Other	4.0%	

Note: All paper results are population weighted/sample corrected.

MODEL ESTIMATION

This study estimated WTP to add connectivity and different levels of automation using an interval regression (IR) model¹³. Wooldridge (2013) provides many details about the IR model, which is briefly described here, for interval response values¹⁴. The key equation is as follows:

$$y_j = \beta' x_j + \varepsilon_i, \tag{1}$$

where subscript "j" denotes an individual observation ($j \in C$) and C is the set of all observations. It is already known that $y_j \in [y_{lj}, y_{rj}]$ (a known interval with lower bound y_{lj} and upper bound y_{rj}); x_i represents a vector of covariates for each respondent; β represents a vector of regression coefficients, to be estimated; and ε_j is the error term, which is assumed to be normally distributed, with mean zero and standard deviation σ . The log-likelihood can therefore be written as follows:

$$\log L = \sum_{j \in C} w_j \log \left\{ \varphi \left(\frac{y_{rj} - \beta' x_j}{\sigma} \right) - \varphi \left(\frac{y_{lj} - \beta' x_j}{\sigma} \right) \right\}, \tag{2}$$

where φ is the standard cumulative normal and w_j is a population-corrected weight for the j^{th} observation.

Additionally, interest in adding connectivity (if affordable), adoption timing of AVs, adoption rates of SAVs under three pricing scenarios (\$1, \$2, and \$3 per mile), future home-location shifts

¹³ Respondents were asked to choose WTP interval (e.g., \$1,500 to \$2,999 to add automation) and also provided with options of "\$3,000 or more" and "\$1,000 or more" in the questions about WTP to add automation and connectivity, respectively. Thus, the response variable is right-censored interval data. Interval regression is an extension of linear regression and reflects all interval boundaries as known values, unlike an ordered probit or logit model specification.

¹⁴ Interval regression can be used to model point, interval, right-censored, and left-censored data types.

(after AVs and SAVs become common modes of transport), and opinions about three congestion pricing policies were estimated using ordered probit (OP) specifications in Stata 12 software (Long and Freese 2006). An example of SAV adoption rates at \$1 per mile is used here to explain the OP model specification (Greene 2012):

$$y_i^* = \beta' x_i + \varepsilon_i, \tag{3}$$

where, y_i^* is respondent i's latent tendency to use SAVs at \$1 per mile; x_i is a vector of explanatory variables for respondent i; β is a vector of regression coefficients, which are to be estimated; and ε_i is a normally-distributed error term.

Three thresholds (μ_1 to μ_4), separating five categories were also estimated, where μ_1 is the threshold between "will never use SAVs" and "will rely less than once a month", μ_2 is the threshold between "will rely less than once a month" and "will rely at least once a month", μ_3 is threshold between "will rely at least once a month" and "will rely at least once a week", and μ_4 is threshold between "will rely at least once a week" and "will rely entirely on SAV fleet". The adoption rate probabilities are as follows:

$$Pr(\text{will never use SAVs}) = Pr(y_i^* \le \mu_1), \tag{4}$$

$$Pr(\text{will rely less than once a month}) = Pr(\mu_1 \le y_i^* \le \mu_2), \tag{5}$$

$$Pr(\text{will rely at least once a month}) = Pr(\mu_2 \le y_i^* \le \mu_3), \tag{6}$$

$$Pr(\text{will rely at least once a week}) = Pr(\mu_3 \le y_i^* \le \mu_4), \tag{7}$$

$$Pr(\text{will rely entirely on SAV fleet}) = Pr(y_i^* \ge \mu_4). \tag{8}$$

In the first step of estimation, subset of explanatory variables from Table 1 is included. In the subsequent steps, the covariates with lowest statistical significance are removed, and this process ends when all remaining covariates have p-values of less than 0.32, which corresponds to a |Z-stat| of more than 1.0. While most of the final specification's covariates have p-values under .05, those with p-values up to 0.32 were because such covariates may offer statistical significance in future studies. Finally, R-square and adjusted R-square values are provided as the goodness-of-fit indicators.

Apart from statistical significance, practical significance is important for understanding the strength or magnitude of relationship between covariates and response variables. Practical significance is quantified here using the change in response values due to a one-standard-deviation rise in each covariate. In the IR models for WTP, covariates with standardized coefficients greater than 0.2 (i.e., those offering a 0.2 standard deviation change in WTP due to 1 SD change in the covariate) are considered practically significant. In the OP model, the choice probabilities are the response variables, so covariates were considered practically significant if the associated probabilities shift by 40 percent or more (i.e., to 1.4 or 0.6 of their original predictions).

Interest in and WTP to add Connectivity

Tables 8 and 9 summarize the OP and IR model estimates of Texans' interest in and WTP for adding connectivity to their vehicles, respectively. These results indicate that more experienced licensed drivers and single individuals tend to be less interested in adding connectivity and exhibit lower WTP for it. Men who are familiar with carsharing, support speed regulation strategies, carry smartphones, drive alone for work, make more social/recreational trips, live further away from downtown, and enjoy higher household income (everything else constant) are estimated to have more interest in adding connectivity (if it is affordable), while those living farther from transit stops appear less interested.

Men with disabilities and/or with bachelor's degrees, who are familiar with TNC's services, travel more, make more business trips, support speed governors, and/or have experienced more moving violations and/or fatal crashes in the past (all other predictors constant), are estimated to have higher WTP for adding connectivity, while older Caucasians with more household members are estimated to place lower value on connectivity. Perhaps the educated, safety-seeking, and tech-savvy respondents are able to perceive the safety benefits of connectivity during their longer travels.

Table 8: Interest in Connectivity Model Results (using Ordered Probit)

		<u> </u>			
Covariates	Coef.	Z-stat	ΔPr_1	ΔPr ₂	ΔPr ₃
Licensed driver (number of years)	-0.032	-4.98	46.1%	2.5%	-28.7%
Support the use of Automated Speed Enforcement?	0.483	3.7	-23.9%	-5.1%	20.2%
Support the use of Speed Governors on all new vehicles?	0.555	4.12	-27.0%	-6.1%	23.1%
Number of fatal (or serious) crashes in past 15 years	0.407	2.08	-50.6%	-16.2%	50.0%
Carry smartphone?	0.541	3	-20.5%	-4.2%	17.0%
Familiar with carsharing?	0.418	2.95	-19.2%	-3.9%	15.8%
Drive alone for work trips?	0.25	1.91	-12.8%	-2.3%	10.2%
More than 2 social (or recreational) trips in past 7 days	0.234	1.82	-11.2%	-2.0%	8.9%
Distance between home and public transit stop (miles)	-0.02	-2.02	13.9%	1.6%	-9.8%
Home and city's downtown are more than 10 miles apart?	0.17	1.35	-8.9%	-1.5%	7.0%
Male?	0.298	2.24	-15.2%	-2.9%	12.3%
Household income (\$)	2.36E-06	1.75	-11.6%	-2.1%	9.2%
Single?	-0.351	-2.25	18.4%	1.9%	-12.7%
Thresholds	Coef.	Std. Dev.			
Not interested vs. Neutral	-0.356	0.282			
Neutral vs. Interested	1.368	0.285			
N _{obs} : 1063 McFadden's R-Square: 0.0	082	McFadder	n's adjuste	d R-Squa	re: 0.070

Note: All ΔPr 's, which are greater than 40%, are in **bold**, and indicate practically significant predictors. All paper results are population weighted/sample corrected.

Table 9: WTP for Connectivity Model Results (using Interval Regression)

Covariates	Coef.	Std. Coef.	Z-stat
Intercept	151.40		4.64
Number of moving violations in past 10 years	10.01	0.129	5.96
Support the use of Speed Governors on all new vehicles?	48.37	0.148	5.04
Number of fatal (or serious) crashes in past 15 years	6.69	0.034	1.95
Number of crashes with only monetary loss in past 15 years	3.79	0.073	1.45
Familiar with UberX or Lyft?	21.03	0.060	2.04
Licensed driver (number of years)	-2.48	-0.216	-3.24
Number of personal business trips in past 7 days	4.48	0.053	2.27
Annual VMT (miles)	1.95E-03	0.068	2.44
No disability?	-17.89	-0.041	-1.23
Household size	-7.20	-0.073	-1.90
Age of Respondent (years)	-0.99	-0.077	-1.74
Male?	10.32	0.042	1.11
White, European white or Caucasian?	-19.66	-0.062	-1.98
Household income (\$)	5.96E-04	0.172	7.16
Bachelor's degree holder	15.03	0.035	1.52
Single?	-17.22	-0.058	-1.48
sigma	138.30		

Note: All Std. Coef., which are greater than 0.2, are in **bold**, and indicate practically significant predictors. All paper results are population weighted/sample corrected.

WTP for Automation Technologies

Table 10 summarizes the IR model specifications of WTP to add Level 2, Level 3, and Level 4 automation. As expected, intercepts in these models rise along with automation level. Respondents who have heard about the Google self-driving car (before taking the survey), support speed governors on all new vehicles, and/or have higher household income (everything else constant) appear willing to pay more for all levels of automation, on average. However, consistent with the findings of the WTP for Connectivity model results (Table 9) and findings in Bansal et al. (2015), older and more experienced licensed drivers tend to place lower value on automation technologies. Perhaps older individuals are finding it difficult to conceive that CAVs are about to hit the roads and licensed drivers who particularly enjoy driving might be worried about sacrificing those elements of driving they find enjoyable.

Individuals with higher annual vehicle miles traveled (VMT) appear willing to pay more for Level 4 automation, but that preference is inverted for those living in more densely populated neighborhoods. Those who live farther from transit stops are found less willing to pay for Level 3 and Level 4 automation. Caucasians' WTP for Level 2 automation is estimated to be lower than that for other ethnicities, as is the case for connectivity, implying that non-Caucasians may be early adopters of CAV technologies. Interestingly, those who experienced more fatal crashes in the past appear significantly interested in paying more for Level 2 and Level 3 automation (as is the case for connectivity); surprisingly, this relationship reverses for those who are familiar with TNC's services.

Table 10: WTP for Automation Technologies Model Results (using Interval Regression)

Covariates (Model 1: WTP for Level 4 Automation)	Coef.	Std. Coef.	Z-stat
Intercept	10300		7.43
Have heard about Google car?	1521	0.099	2.64
Support the use of Speed Governors on all new vehicles?	1755	0.120	3.32
Have heard about CVs?	931.1	0.054	1.28
Licensed driver (number of years)	-61.07	-0.092	-1.27
Distance between home and public transit stop (miles)	-75.18	-0.061	-1.60
Annual VMT (miles)	9.96E-02	0.078	2.40
Age of Respondent (years)	-104.60	-0.229	-2.71
Household income (\$)	1.04E-02	0.078	1.81
Single?	1000	0.064	1.63
Population density (per square mile)	-0.11	-0.046	-1.29
Sigma (σ)	6961		
N _{obs} : 755 McFadden's R-Square: 0.035	McFadden's adju	sted R-Squar	e: 0.029
Covariates (Model 2: WTP for Level 3 Automation)	Coef.	Std. Coef.	Z-stat
Intercept	7179		7.17
Have heard about Google car?	1094	0.099	2.58
Support the use of Speed Governors on all new vehicles?	1229	0.114	3.27
Number of fatal (or serious) crashes in past 15 years	438.6	0.134	4.82
Familiar with UberX or Lyft?	-506.8	-0.041	-1.21
Licensed driver (number of years)	-54.56	-0.118	-1.52

Number of personal business trips in past 7 days	96.91	0.037	1.06				
Distance between home and public transit stop (miles)	-42.49	-0.049	-1.26				
Distance between home and city's downtown (miles)	40.98	0.045	1.22				
Age of Respondent (years)	-73.12	-0.217	-2.45				
Household income (\$)	7.53E-03	0.069	1.79				
Sigma (σ	4792						
Nobs: 755 McFadden's R-Square: 0.044	McFadden's adj	usted R-Squar	e: 0.039				
Covariates (Model 3: WTP for Level 2 Automation)	Coef.	Std. Coef.	Z-stat				
Intercept	5059		6.65				
Have heard about Google car?	896.8	0.101	2.45				
Support the use of Speed Governors on all new vehicles?	1241	0.144	3.94				
Number of fatal (or serious) crashes in past 15 years	554.6	0.212	8.36				
Familiar with UberX or Lyft?	-750.7	-0.076	-2.24				
Licensed driver (number of years)	-51.35	-0.140	-1.80				
Household size over 3?	-501.4	-0.053	-1.57				
Age of Respondent (years)	-38.91	-0.245	-1.63				
White, European white or Caucasian?	-467.8	-0.052	-1.39				
Household income (\$)	5.55E-03	0.064	1.69				
Sigma (σ)	3743						
N _{obs} : 755 McFadden's R-Square: 0.048 McFadden's adjusted R-Square: 0.048							

Note: All Std. Coef., which are greater than 0.2, are in **bold**, and indicate practically significant predictors. All paper results are population weighted/sample corrected.

Adoption Timing of Autonomous Vehicles

Table 11 summarizes OP model estimates of AV adoption timings (i.e., will never adopt an AV, will adopt AVs when 50% of friends adopt, when 10 % of friends adopt, or as soon as available in the market). The adoption timing of disabled individuals and bachelor's degree holders who support speed-regulation strategies, are familiar with carsharing, travel more, have more than one worker in the household, and live in a neighborhood with a higher density of employed individuals—all other predictors constant—are less likely to depend on friends' adoption rates. In contrast, the adoption timing of older, single, and Caucasian respondents who have larger households and live farther from bus stop in more densely populated neighborhoods may be more dependent on friends' adoption rates. These estimates appear consistent with the WTP for Automation Technologies model results (in Table 10)¹⁵, in that adoption timing of those who indicate higher WTP for AVs is estimated to depend less on their friends' adoption rates.

Table 11: Adoption Timing of Autonomous Vehicles Model Results (using Ordered Probit)

Covariates	Coef.	Z-stat	ΔPr_1	ΔPr_2	ΔPr ₃	ΔPr ₄
Support the use of Automated Speed Enforcement?	0.455	1.82	-17.7%	3.6%	23.3%	43.0%
Support the use of Speed Governors on all new vehicles?	0.365	1.99	-14.2%	3.1%	18.5%	33.3%
Have heard about CVs?	0.362	1.52	-10.8%	2.5%	13.9%	24.4%
Familiar with carsharing?	0.336	2.19	-12.0%	2.8%	15.6%	27.6%
Distance between home and public transit stop (miles)	-0.051	-2.44	26.1%	-9.3%	-29.1%	-41.9%
Annual VMT (miles)	3.13E-05	1.74	-15.3%	3.3%	20.1%	36.4%
No disability?	-0.454	-1.65	11.8%	-3.7%	-13.9%	-21.5%
Household size	-0.109	-1.69	12.4%	-3.9%	-14.6%	-22.5%

¹⁵ As an exception, single respondents are estimated to have higher WTP to add Level 4 automation (other attributes held constant), but their adoption timing depends more on their friends' adoption rates.

More than 1 worker in household?	0.259	1.41	-10.1%	2.4%	12.9%	22.6%
Age of Respondent (years)	-0.025	-2.53	33.9%	-12.7%	-36.6%	-51.0%
White, European white or Caucasian?	-0.273	-1.32	10.6%	-3.3%	-12.5%	-19.4%
Bachelor's degree holder	0.260	1.50	-10.1%	2.4%	12.9%	22.6%
Single?	-0.385	-1.83	14.5%	-4.7%	-16.9%	-25.8%
Population density (per square mile)	-1.76E-04	-1.47	48.8%	-20.1%	-49.6%	-65.0%
Employed and over 16 years of age (per square mile)	1.96E-04	1.09	-27.2%	24.2%	22.7%	33.3%
Thresholds	Coef.	Std.				
Never vs. 50% friends adopt	-1.898	0.665				
50% friends adopt vs. 10% friends adopt	-0.303	0.688				
10% friends adopt vs. As soon as available	0.555	0.738				
Nobs: 1 088 McFadden's R-Square:	McFadde	en's adiust	ed R-Saua	re: 0 046		

Note: All ΔPr 's, which are greater than 40%, are in **bold**, and indicate practically significant predictors. All paper results are population weighted/sample corrected.

SAV Adoptions Rates under Different Pricing Scenarios

Table 12 summarizes the OP model estimates of SAV adoption rates (i.e., relying on an SAV fleet less than once a month, at least once a month, at least once a week, or entirely) under different pricing scenarios (\$1 per mile [Model 1], \$2 per mile [Model 2], and \$3 per mile [Model 3]). Respondents who experienced fatal crashes in the past, support speed regulation strategies, have heard about CVs, live farther from downtown, and have more workers in households, all other predictors constant, appear ready to use SAVs frequently. In contrast, and consistent with Table 10's WTP for Automation Technologies model findings, Caucasians who are licensed (or more experienced) drivers and live farther from transit stops are estimated to use SAVs less frequently in all three pricing scenarios 16.

It is worth noting that even unemployed and lower income households (with annual household income less than \$30,000) are estimated to use SAVs more frequently at \$1 per mile; perhaps SAVs are affordable for these individuals at this price. Those who travel more also expect to use SAVs more frequently at \$1 per mile, since they may readily visualize the cost-reduction benefits at this lower price. Respondents who have experienced more moving violations in the past are expected to use SAVs frequently at \$1 and \$2 per mile; perhaps they can visualize that SAVs can save them from future violations¹⁷. Interestingly, married respondents who are familiar with UberX (everything else constant) are estimated to use SAVs less frequently, but those who make more social/recreation trips are expected to use SAVs frequently at even \$2 and \$3 per mile (more than what carsharing companies and UberX charge). Perhaps those who know about TNC's services are not willing to pay additional charges to enjoy SAVs' additional utilities; the vehicle ownership level (not controlled here) of married couples might be discouraging them from using SAVs at higher prices. Lastly, perhaps bigger households are likely to use SAVs as an alternative to a second vehicle and disabled individuals are able to perceive the maximum utility of SAVs, and thus both demographic groups are likely to use SAVs more frequently, even at \$3 per mile

¹⁶ Since household vehicle ownership is not controlled here, the respondents showing negative inclination towards SAVs may have higher vehicle ownership, on average.

¹⁷ However, even respondents who experienced more moving violations in the past do not attach statistical significance to the SAVs' utility of saving them from future violations at \$3 per mile.

Table 12: SAV Adoption Rates under Different Pricing Scenarios (using Ordered Probit)

			`				
Covariates (Model 1: \$1 per mile)	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅
Number of moving violations in past 10 years	0.081	1.91	-32.3%	-16.7%	-4.8%	8.0%	20.6%
Support the use of Automated Speed Enforcement?	0.407	2.11	-32.3%	-16.7%	-4.7%	8.0%	20.5%
Support the use of Speed Governors on all new vehicles?	1.040	5.49	-65.4%	-40.3%	-15.0%	18.4%	59.7%
At least 1 fatal (or serious) crash in past 15 years?	0.615	1.64	-29.2%	-14.9%	-4.2%	7.1%	18.1%
Have heard about CVs?	0.501	1.64	-30.9%	-15.9%	-4.5%	7.6%	19.5%
Distance between home and public transit stop (miles)	-0.038	-2.15	47.8%	19.0%	3.3%	-9.3%	-18.9%
Distance between home and city's downtown (miles)	0.025	1.66	-24.9%	-12.5%	-3.4%	6.0%	14.9%
Annual VMT more than 15,000 miles?	0.298	1.35	-20.2%	-9.9%	-2.6%	4.8%	11.7%
Number of workers in household	0.227	2.34	-34.5%	-18.0%	-5.2%	8.6%	22.4%
Male?	-0.257	-1.29	26.4%	11.2%	2.2%	-5.5%	-11.5%
Have U.S. driver license?	-1.163	-3.15	72.7%	27.2%	4.2%	-13.4%	-25.9%
White, European white or Caucasian?	-0.419	-2.13	45.0%	18.0%	3.2%	-8.8%	-18.0%
Household income less than \$30,000?	0.425	2.11	-30.4%	-15.6%	-4.4%	7.5%	19.0%
Unemployed?	0.508	2.10	-31.4%	-16.2%	-4.6%	7.7%	19.8%
Thresholds	Coef.	Std.					
Never use vs. Rely less than once a month	-2.510	0.431					
Rely less than once a month vs. Rely at least once a month	-0.769	0.412					
Rely at least once a month vs. Rely at least once a week	0.510	0.411					
Rely at least once a week vs. Rely entirely on SAV fleet	2.409	0.455					
Nobe: 730 McFadden's R-Square: 0.113 McFadden's adjusted R-Square: 0.09							

Nobs: 730 McFadden's R-Square: 0.113 McFadden's adjusted R-Square: 0.097

Covariates (Model 2: \$2 per mile)	Coef.	Z-stat	ΔPr_1	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅
Licensed driver (number of years)	-0.017	-1.60	22.8%	6.7%	-2.3%	-14.1%	-21.2%
Number of moving violations in past 10 years	0.093	1.90	-22.4%	-8.6%	0.9%	16.3%	31.5%
Support the use of Automated Speed Enforcement?	0.515	2.40	-24.5%	-9.5%	0.9%	17.9%	35.1%
Support the use of Speed Governors on all new vehicles?	0.899	4.02	-40.3%	-17.4%	0.2%	31.2%	70.1%
Number of fatal (or serious) crashes in past 15 years	0.179	1.62	-28.1%	-11.2%	0.8%	20.8%	42.1%
Have heard about CVs?	0.640	2.47	-23.6%	-9.1%	0.9%	17.2%	33.5%
Familiar with UberX or Lyft?	-0.527	-2.24	26.8%	7.6%	-2.8%	-16.3%	-24.1%
Drive alone for work trips?	-0.330	-1.61	17.8%	5.4%	-1.7%	-11.2%	-17.2%
More than 2 social (or recreational) trips in past 7 days	0.401	1.95	-18.8%	-7.0%	0.9%	13.5%	25.4%
Distance between home and public transit stop (miles)	-0.057	-2.90	37.6%	10.1%	-4.3%	-22.1%	-31.3%
Distance between home and city's downtown (miles)	0.036	2.17	-20.9%	-7.9%	0.9%	15.1%	28.9%
Number of workers in household	0.277	2.21	-25.4%	-9.9%	0.9%	18.6%	36.9%

Older than 54 years?	-0.498	-2.05	25.6%	7.4%	-2.7%	-15.7%	-23.3%
White, European white or Caucasian?	-0.379	-1.92	20.7%	6.1%	-2.0%	-12.9%	-19.5%
Married?	-0.383	-1.98	21.4%	6.3%	-2.1%	-13.3%	-20.1%
Thresholds	Coef.	Std.					
Never use vs. Rely less than once a month	-1.435	0.443					
Rely less than once a month vs. Rely at least once a month	0.040	0.429					
Rely at least once a month vs. Rely at least once a week	1.302	0.444					
Rely at least once a week vs. Rely entirely on SAV fleet	3.191	0.536					
N _{obs} : 730 McFadden's R-Square:	0.123		Mo	cFadden's	adjusted l	R-Square:	0.108
Covariates (Model 3: \$3 per mile)	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅
Licensed driver (number of years)	-0.018	-2.28	16.1%	1.7%	-7.4%	-19.2%	-24.9%
Support the use of Automated Speed Enforcement?	0.475	2.37	-16.4%	-3.4%	6.5%	23.3%	36.8%
Support the use of Speed Governors on all new vehicles?	0.895	4.34	-30.1%	-7.7%	10.7%	46.0%	81.8%
Number of fatal (or serious) crashes in past 15 years	0.191	3.61	-21.8%	-4.9%	8.3%	31.9%	52.7%
Have heard about CVs?	0.874	3.03	-22.9%	-5.3%	13.6%	33.7%	36.2%
Familiar with UberX or Lyft?	-0.259	-1.38	8.6%	1.1%	-3.8%	-10.6%	-14.4%
Number of social (or recreational) trips in past 7 days	0.080	1.68	-11.0%	-2.1%	4.5%	15.1%	23.1%
Distance between home and public transit stop (miles)	-0.056	-3.01	24.1%	2.0%	-11.4%	-27.5%	-34.5%
Distance between home and city's downtown (miles)	0.032	1.86	-13.4%	-2.6%	5.4%	18.8%	29.1%
No disability?	-0.495	-1.72	12.2%	1.4%	-5.5%	-14.8%	-19.6%
Household size over 3?	0.291	1.49	-9.6%	-1.8%	3.9%	13.1%	19.7%
Number of workers in household	0.127	1.17	-8.7%	-1.6%	3.6%	11.8%	17.7%
White, European white or Caucasian?	-0.661	-3.40	24.5%	2.0%	-11.6%	-27.9%	-34.9%
Married?	-0.452	-2.33	16.9%	1.7%	-7.8%	-20.0%	-26.0%
Thresholds	Coef.	Std.					
Never use vs. Rely less than once a month	-0.828	0.475					
Rely less than once a month vs. Rely at least once a month	0.326	0.479					
Rely at least once a month vs. Rely at least once a week	1.632	0.490					
Rely at least once a week vs. Rely entirely on SAV fleet	3.381	0.606					
N _{obs} : 730 McFadden's R-Square: 0.121 McFadden's adjusted R-Square: 0.100							: 0.105

Note: All Δ Pr's, which are greater than 40%, are in **bold**, and indicate practically significant predictors. All paper results are population weighted/sample corrected.

Home Location Shifts due to AVs and SAVs

Table 13 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)¹⁸ after AVs and SAVs become common modes of transport. Bachelor's degree holders, single individuals, and full-time workers who support speed governors, own at least a vehicle with Level 2 automation, have experienced more fatal crashes in past, and live farther from a city center—all other attributes constant—appear more likely to shift closer to the city center. Perhaps these individuals are excited about higher density of low-cost SAVs near city center. However, respondents who live farther from transit stops, make more social/recreation trips, and are familiar with UberX (everything else constant) are predicted to shift farther from the city center. Perhaps these individuals are concerned about higher land prices in the urban neighborhoods, and are keen to enjoy the benefits of moving to suburban areas after AVs and SAVs become common modes of transport.

Table 13: Home Location Shifts due to AVs and SAVs Model Results (using Ordered Probit)

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Covariates	Coef.	Z-stat	ΔPr_1	ΔPr_2	ΔPr ₃			
Own a vehicle?	-1.386	-3.25	28.9%	-1.6%	-34.7%			
Own at least a vehicle with Level 2 automation?	-1.443	-3.22	72.6%	-0.8%	-39.7%			
Support the use of Speed Governors on all new vehicles?	-0.466	-2.06	39.1%	-0.3%	-26.4%			
Number of fatal (or serious) crashes in past 15 years	-0.170	-1.75	32.4%	-0.6%	-27.6%			
Familiar with UberX or Lyft?	0.336	1.44	-21.0%	-0.2%	23.0%			
Distance from city centre (miles)	-0.068	-3.65	79.0%	-0.9%	-41.8%			
Drive alone for work trips?	0.291	1.20	-19.5%	-0.2%	20.9%			
Number of social (or recreational) trips in past 7 days	0.069	1.38	-18.1%	-0.2%	19.1%			
Distance between home and public transit stop (miles)	0.049	2.59	-37.2%	-0.7%	49.1%			
Older than 54 years?	-0.464	-2.17	38.2%	-0.2%	-25.5%			
Male?	-0.428	-2.03	36.4%	-0.2%	-24.6%			
White, European white or Caucasian?	-0.349	-1.37	27.4%	-0.1%	-19.7%			
Bachelor's degree holder	-0.263	-1.32	20.8%	-0.1%	-15.7%			
Full time worker?	-0.445	-1.65	36.9%	-0.2%	-24.9%			
Single?	-0.431	-1.63	33.6%	-0.2%	-23.2%			
Thresholds	Coef.	Std.						
Shift closer vs. stay at the same location	-4.992	0.589						
stay at the same location vs. shift farther	0.103	0.518						
Nobs: 1088 McFadden's R-Square: 0.112 McFadden's adjusted R-Square: 0.087								

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¹⁸ This model alone can obtain inferences about two groups' characteristics: those "who want to shift closer to the city center or stay at the same location" and those "who want to shift farther from the city center or stay at the same location." However, to appreciate the characteristics of population groups "who want to shift closer to the city center" and "who want to shift farther from the city center", a new binary logit model was estimated, so as to explore the individual characteristics of those "who want to stay at the same location" after AVs and SAVs become common modes of transport. For example, according to OP model estimates, those who are familiar with UberX are either likely to shift farther from the city center or stay at the same location, but the binary logit model suggests that these individuals are likely to shift. This new binary logit model clarifies that these individuals are expected to shift farther from the city center.

Note: All ΔPr 's, which are greater than 40%, are in **bold**, and indicate practically significant predictors. All paper results are population weighted/sample corrected.

Support for Tolling Policies

Table 14 summarizes the OP model estimates of respondents' opinions (i.e., definitely not support, probably not support, do not know, probably support, or definitely support) about three tolling policies¹⁹. In Policy 1, revenue from tolled congested highways is used to reduce property taxes; in Policy 2, revenue from tolled congested highways is distributed evenly among Texans; in Policy 3, time varying tolls are enabled on all congested roadways. Results indicate that Caucasians who are licensed (or more experienced) drivers and live farther from transit stops, everything else constant, are likely to show refusal for all tolling policies. Perhaps these individuals are concerned that they would be the primary toll payers²⁰, and only others would benefit from these three policies. Interestingly, bachelor's degree holders who live farther from downtown are estimated to be more likely to support Policies 1 and 2; and full-time workers who have more children in their household are more likely to support Policies 2 and 3. Older respondents are predicted to be less supportive of Policies 1 and 3. Respondents whose households own at least one vehicle and live in populous areas (everything else constant) specifically are less supportive of Policy 3, but those who live in neighborhoods with more employed individuals are more likely to support this policy.

¹⁹ Safety- and tech-based predictors were not used in these models' specifications.

²⁰ However, individuals who travel more, all other attributes remaining equal, are more likely to support tolling-related Policies 2 and 3.

 Table 14: Support for Tolling Policies Model Results (using Ordered Probit)

Table 14: Support for Tolling Policies Model Results (using Ordered Probit)										
Covariates (Model 1: Toll Congested Highways if	Coef.	Z-stat	ΔPr ₁	ΔPr_2	ΔPr ₃	ΔPr ₄	ΔPr ₅			
Reduce Property Tax)	0.445			44.4	0.051		22.2			
Licensed driver for more than 20 years?	-0.462	-2.21	27.8%	11.1%	-0.9%	-16.3%	-32.2%			
More than 2 social (or recreational) trips in past 7 days	0.295	1.69	-14.7%	-7.5%	-0.9%	9.5%	24.2%			
Distance between home and public transit stop (miles)	-0.041	-2.53	31.1%	12.2%	-1.2%	-18.1%	-35.3%			
Distance between home and city's downtown (miles)	0.030	2.09	-19.1%	-10.0%	-1.4%	12.4%	32.7%			
Household size over 3?	-0.300	-1.50	16.0%	6.8%	-0.2%	-9.6%	-20.2%			
Number of workers in household	0.228	2.27	-22.6%	-12.0%	-1.9%	14.8%	40.1%			
Older than 54 years?	-0.474	-1.91	27.6%	11.0%	-0.9%	-16.2%	-32.1%			
White, European white or Caucasian?	-0.553	-2.37	32.3%	12.5%	-1.3%	-18.7%	-36.2%			
Bachelor's degree holder	0.365	2.33	-19.0%	-9.9%	-1.4%	12.3%	32.5%			
Thresholds	Coef.	Std.								
Definitely not support vs. Probably not support	-1.372	0.331		-						
Probably not support vs. Do not know	-0.886	0.321								
Do not know vs. Probably Support	0.268	0.325								
Probably support vs. Definitely support	1.548	0.345								
N _{obs} : 1,088 McFadden's R-Square: 0.049 McFadden's adjusted R-Square: 0.										
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11005 13000 INTEL AUGUS S R	5quare: 0.01.	,		ivici addei	r s aajust	cu it squu	10.041			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues)	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years)										
Covariates (Model 2: Toll Congested Highways if Distribute Revenues)	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years)	Coef0.043	Z-stat -5.74	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles)	Coef. -0.043 -0.051	Z-stat -5.74 -4.00	ΔPr ₁ 62.6% 36.9%	ΔPr ₂ 15.2% 10.8%	ΔPr ₃ -8.7% -4.0%	ΔPr ₄ -36.7% -23.1%	ΔPr ₅ -63.6% -45.2%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles)	Coef0.043 -0.051 0.026	Z-stat -5.74 -4.00 1.83	ΔPr ₁ 62.6% 36.9% -15.9%	ΔPr ₂ 15.2% 10.8% -6.8%	ΔPr ₃ -8.7% -4.0% 0.2%	ΛPr 4 -36.7% -23.1% 11.5%	ΔPr 5 -63.6% -45.2% 31.1%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles)	Coef. -0.043 -0.051 0.026 2.63E-05	Z-stat -5.74 -4.00 1.83 2.00	ΔPr ₁ 62.6% 36.9% -15.9% -16.7%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2%	ΔPr ₃ -8.7% -4.0% 0.2% 0.1%	ΔPr ₄ -36.7% -23.1% 11.5% 12.1%	ΔPr ₅ -63.6% -45.2% 31.1% 33.1%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian?	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460	Z-stat -5.74 -4.00 1.83 2.00 -2.93	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2% 7.9%	ΔPr ₃ -8.7% -4.0% 0.2% 0.1% -2.2%	ΔPr ₄ -36.7% -23.1% 11.5% 12.1% -16.1%	ΔPr 5 -63.6% -45.2% 31.1% 33.1% -33.5%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian? Number of children in household	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460 0.160	Z-stat -5.74 -4.00 1.83 2.00 -2.93 2.05	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8% -17.0%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2% 7.9% -7.3%	-8.7% -4.0% 0.2% 0.1% -2.2% 0.1%	APr ₄ -36.7% -23.1% 11.5% 12.1% -16.1% 12.3%	ΔPr 5 -63.6% -45.2% 31.1% 33.1% -33.5% 33.7%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian? Number of children in household Bachelor's degree holder	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460 0.160 0.227	Z-stat -5.74 -4.00 1.83 2.00 -2.93 2.05 1.50	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8% -17.0% -11.5%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2% 7.9% -7.3% -4.7%	-8.7% -4.0% 0.2% 0.1% -2.2% 0.19 0.2%	ΔPr ₄ -36.7% -23.1% 11.5% 12.1% -16.1% 12.3% 8.2%	ΔPr ₅ -63.6% -45.2% 31.1% 33.1% -33.5% 33.7% 21.5%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian? Number of children in household Bachelor's degree holder Full time worker?	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460 0.160 0.227 0.307	Z-stat -5.74 -4.00 1.83 2.00 -2.93 2.05 1.50 1.89	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8% -17.0% -11.5%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2% 7.9% -7.3% -4.7%	-8.7% -4.0% 0.2% 0.1% -2.2% 0.19 0.2%	ΔPr ₄ -36.7% -23.1% 11.5% 12.1% -16.1% 12.3% 8.2%	ΔPr ₅ -63.6% -45.2% 31.1% 33.1% -33.5% 33.7% 21.5%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian? Number of children in household Bachelor's degree holder Full time worker? Thresholds	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460 0.160 0.227 0.307 Coef.	Z-stat -5.74 -4.00 1.83 2.00 -2.93 2.05 1.50 1.89 Std.	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8% -17.0% -11.5% -15.2%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2% 7.9% -7.3% -4.7% -6.4%	APr ₃ -8.7% -4.0% 0.2% 0.1% -2.2% 0.1% 0.2% 0.2%	APr4 -36.7% -23.1% 11.5% 12.1% -16.1% 12.3% 8.2% 10.9%	APrs -63.6% -45.2% 31.1% 33.1% -33.5% 33.7% 21.5% 29.5%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian? Number of children in household Bachelor's degree holder Full time worker? Thresholds Definitely not support vs. Probably not support	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460 0.160 0.227 0.307 Coef1.780	Z-stat -5.74 -4.00 1.83 2.00 -2.93 2.05 1.50 1.89 Std. 0.280	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8% -17.0% -11.5% -15.2%	ΔPr ₂ 15.2% 10.8% -6.8% -7.2% 7.9% -7.3% -4.7% -6.4%	-8.7% -4.0% 0.2% 0.1% -2.2% 0.19 0.2% 0.2%	ΔPr ₄ -36.7% -23.1% 11.5% 12.1% -16.1% 12.3% 8.2% 10.9%	ΔPr ₅ -63.6% -45.2% 31.1% 33.1% -33.5% 21.5% 29.5%			
Covariates (Model 2: Toll Congested Highways if Distribute Revenues) Licensed driver (number of years) Distance between home and public transit stop (miles) Distance between home and city's downtown (miles) Annual VMT (miles) White, European white or Caucasian? Number of children in household Bachelor's degree holder Full time worker? Thresholds Definitely not support vs. Probably not support Probably not support vs. Do not know	Coef. -0.043 -0.051 0.026 2.63E-05 -0.460 0.160 0.227 0.307 Coef1.780 -1.086	Z-stat -5.74 -4.00 1.83 2.00 -2.93 2.05 1.50 1.89 Std. 0.280 0.272	ΔPr ₁ 62.6% 36.9% -15.9% -16.7% 24.8% -17.0% -11.5% -1-5.2%	15.2% 10.8% -6.8% -7.2% 7.9% -7.3% -4.7% -6.4%	-8.7% -4.0% 0.2% 0.1% -2.2% 0.1% 0.2%	ΔPr ₄ -36.7% -23.1% 11.5% 12.1% -16.1% 12.3% 8.2% 10.9%	ΔPr ₅ -63.6% -45.2% 31.1% 33.1% -33.5% 21.5% 29.5%			

Covariates (Model 3: Time-varying tolls on All Congested Roadways)	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄	ΔPr ₅
Own a vehicle?	-0.754	-1.35	23.5%	10.2%	-0.7%	-13.7%	-27.7%
More than 2 personal business trips in past 7 days?	0.293	1.14	-14.1%	-7.3%	-0.4%	9.4%	22.9%
Distance between home and public transit stop (miles)	-0.024	-1.44	19.8%	8.7%	-0.5%	-11.7%	-24.0%
Annual VMT (miles)	1.92E-05	1.48	-14.4%	-7.5%	-0.4%	9.6%	23.6%
Age of Respondent (years)	-0.015	-1.84	33.8%	13.9%	-1.4%	-19.0%	-36.8%
Have U.S. driver license?	0.342	1.00	-10.6%	-5.4%	-0.2%	6.9%	16.7%
White, European white or Caucasian?	-0.903	-4.33	62.8%	22.7%	-4.3%	-32.4%	-56.4%
Number of children in household	0.168	1.91	-20.6%	-11.1%	-0.9%	14.0%	35.8%
Full time worker?	0.265	1.66	-15.3%	-8.0%	-0.5%	10.2%	25.3%
Population density (per square mile)	-2.51E-04	-1.41	36.7%	34.6%	-15.6%	-57.7%	-42.3%
Employed and over 16 years of age (per square mile)	3.96E-04	1.83	-21.1%	-22.3%	-24.2%	10.9%	25.9%
Thresholds	Coef.	Std.					
Definitely not support vs. Probably not support	-2.486	0.492					
Probably not support vs. Do not know	-1.949	0.498					
Do not know vs. Probably Support	-0.411	0.508					
Probably support vs. Definitely support	1.185	0.539					
Nobs: 1,088 McFadden's R-S	Square: 0.057			McFaddei	n's adjust	ed R-Squa	re: 0.048

Note: All ΔPr's, which are greater than 40%, are in **bold**, and indicate practically significant predictors. All results are population weighted/sample corrected.

CONCLUSIONS

This study used ordered probit (OP) and interval regression (IR) models to understand the impact of demographics, built-environment factors, travel characteristics, safety-related opinions, and other attributes on Texans' adoption of and interest in CAV technologies and SAVs. Results suggest that more experienced licensed drivers have greater interest in and higher WTP for adding DSRC-based connectivity to their current and existing vehicles; while relatively older people found to have lower WTP for all levels of automation. Perhaps more experienced drivers are better able to assess safety benefits of connectivity, and older individuals may find it difficult to visualize that AVs are no longer visions of some very distant future. Similarly, AV adoption by older persons living farther from bus stops but in denser neighborhoods is estimated to depend more on friends' adoption rates; and those who tend to support automated speed enforcement appear more likely to be early adopters. Interestingly, those who support speed governors are predicted to use SAVs frequently, at all three prices (\$1 per mile, \$2 per mile, and \$3 per mile). Finally, those in households owing at least one vehicle with Level 2 automation and living farther from city center appear more likely to shift their residences closer to the city center, in order to enjoy access to higher frequency of low-cost SAVs.

Knowledge of practically significant explanatory variables can allow policymakers to identify the regions with low and high penetration rates for future CAV technologies. Awareness campaigns may be valuable for low-penetration locations and household types, while high penetration regions may be equipped earlier with complementary hardware and software (e.g., to automate signal use and/or warn of dangerous conditions). These model specifications can be instrumental in forecasting long-term adoption of CAV technologies and SAVs (see, e.g., Bansal and Kockelman [2015]), as well as evolving VMT²¹. This will not only help auto manufacturers and investors in choosing top automation technologies for investment, but will also help policymakers plan for infrastructure adjustments. For example, if fleets of electric SAVs (like Google's famous prototype) become available, charging infrastructure and new parking systems may be critical for high usage rates. Moreover, VMT forecasts can inform system managers and planners about induced or latent travel demands due to CAVs' added convenience, prompting credit-based or other congestion pricing policies (Gulipalli and Kockelman 2008).

Population-weighted summary statistics suggest that around 41% of Texans are not yet ready to use SAVs and only 7.3% hope to rely entirely on an SAV fleet, even at \$1 per mile. The average WTP for Level 2, Level 3, and Level 4 automation and connectivity are currently \$2,910, \$4,607, \$7,589, and \$127, respectively. Talking to other passengers and looking out the window are the Texans' top two activity-picks while riding in Level 4 AVs. Affordability and equipment failure are the Texans' top two concerns regarding AVs; the two least concerning aspects are learning how to use AVs and, surprisingly, potential privacy breaches. Texans expect that AVs can help provide better fuel economy and also decrease crashes: 53.9% and 53.1% of the respondents, respectively, indicated that these benefits will be very significant. Texans are most likely to support adaptive traffic signal timing and least likely to support real-time adjustment in

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²¹ Respondents' (population-corrected) expectation of an increase in the number of long-distance trips (over 50 miles, one-way) they make each month, after having access to/adopting an AV, is 1.3 (long-distance trips per person, per month), suggesting a 156% increase across the (population-corrected) sample's total long-distance tripmaking. In other words, long-distance trip-making frequencies are predicted to more than double, following access to AVs.

parking prices (when 80% of vehicles are connected). On average, Texans rank safety as the most important and climate change as the least important area of improvement in automobile technologies.

However, in the current scenario, AVs and SAVs are less likely to affect Texans' decisions about moving closer to or farther from the city center: about 81.5% indicated an intention or desire to stay at their current locations. Americans are at early stage in understanding CAV technologies, so opinions are likely to change rapidly over the coming years, with more awareness of emerging technologies, leading to changes in VMT and possibly land use patterns, suggesting a need for effective lane-, land-, and/or SAV-pricing policies to moderate congestion, energy, and other potentially negative impacts. More data, over time, in more locations, will be helpful in preparing communities for this major transition in our transportation systems.

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