Transportation (2018) 45:641–675
https://doi.org/10.1007/s11116-016-9745-z

Are we ready to embrace connected and self-driving vehicles? A case study of Texans

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Published online: 19 November 2016

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, the introduction of these technologies is accompanied by uncertainties in their effects on the carsharing market and land use patterns, and raises the need for tolling policies to appease the travel demand induced due to the increased convenience. To these ends, this study surveyed 1088 respondents across Texas to understand their opinions about smart vehicle technologies and related decisions. The key summary statistics indicate that Texans are willing to pay (WTP) \$2910, \$4607, \$7589, 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 histories, and response variables, including willingness to pay for CAV technologies, adoption rates of shared AVs at different pricing points, home location shift decisions, adoption timing of automation technologies, and opinions about various tolling policies. The practically significant relationships indicate that more experienced licensed drivers and older people associate lower WTP values with all new vehicle technologies. Such parameter estimates help not only in forecasting long-term adoption of CAV technologies, but also help transportation planners in understanding the characteristics of regions with high or low future-year CAV adoption levels, and subsequently, develop smart strategies in respective regions.

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Keywords Connected and autonomous vehicles · Ordered probit · Interval regression · Public opinion survey · Willingness to pay

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. The complexity and ambiguity of the transportation future that CAV technologies are about to bring is overwhelming. The public is an important stakeholder in determining how this future will evolve. Many researchers (e.g., Casley et al. 2013; Howard and Dai 2013; Schoettle and Sivak 2014, 2015, Kyriakidis et al. 2015; Haboucha et al. 2015; Krueger et al. 2016; Bansal et al. 2016), private firms (Accenture Research 2011; Cisco Systems 2013; Ipsos MORI 2014; Power 2015); Continental (Sommer 2013; KPMG 2013), and others, such as NerdWallet (Danise 2015) and Insurance.com (Vallet 2014), have conducted public opinion surveys regarding AVs. A detailed review of these studies can be found in "Literature review" section.

To the best of our knowledge, only Howard and Dai (2013), Bansal et al. (2016), Haboucha et al. (2015), and Krueger et al. (2016) have gone beyond summary statistics and pairwise correlation analysis to uncover connections between individuals' opinions about CAVs (and SAVs) and their characteristics. To this end, this study conducted a Texas-wide survey and then estimated econometric models to understand multivariate relationships between Texans' opinions of CAV technologies and their demographic and home-location characteristics.[1] Revealing these relationships helps identify key determinants that make individuals favor or reject these technologies. Such understanding provides consumer demand insights, facilitating fleet forecasting [as pursued by Bansal and Kockelman (2016)], and helps policymakers and public officials make infrastructure investment decisions, address legal and safety issues, and support various other aspects of CAV systems.

To this end, there are many motivations for the models estimated in this study. The U.S. government anticipates an evolution toward CAV technologies, but their rate of adoption will depend greatly on technology costs and consumers' willingness to pay (WTP). Bansal and Kockelman (2016) assumed a fixed annual increment in WTP of the individuals while forecasting the long-term adoption of these technologies. This paper offers a multivariate relationship between WTP and each individual's characteristics (e.g., travel patterns and demographics)[2] to describe current preferences while offering a more realistic forecast of WTP evolution over coming years, enabling more realistic forecasts of CAV adoption rates. Since adoption forecasting is not the scope of this study, individual characteristics that cannot be forecasted (such as familiarity with ride-sharing services and opinions about speed governors) are also included, to provide more behavioral insights. Such insights are advantageous for the policymakers because currently little is known about public perception of CAVs.

[1] The survey asked questions about benefits of and concerns of CAVs, crash history, opinions about speed regulations, willingness to pay (WTP) for and interest in CAV technologies, demographics, travel patterns, among many others. Please see later section about survey designing to know more about the details of the survey instrument.

[2] Please see Tirumalachetty et al. (2009) for micro-simulation of demographics.

This work hypothesizes that individuals may be more interested in buying CAV technologies if their neighbors, friends, and/or relatives already own or use such technologies, presumably due to a sense of social status and/or greater trust via second-hand experience. Understanding such preferences can help deliver more realistic forecasts of CAV technology adoption.[3] Thus, this study estimates individuals' adoption timing of CAVs, with respondents given the choice to never adopt an AV, adopt an AV when at least 10% or at least 50% of neighbors, friends or relatives own it, or as soon as it is available in the market.

Many recent studies have investigated shared AVs (SAVs) as a new mode of transport (Burns et al. 2013; Fagnant et al. 2015; Chen et al. 2016; Liu et al. 2016; Loeb et al. 2016). Such on-demand "autonomous taxis" enable short-term rental while lowering AV access issues and costs (Fagnant and Kockelman 2014). A higher density of low-cost SAVs in the city center may motivate many people to move toward the region's core, but the ability to make better use of one's travel time while riding in an AV may encourage a move to the suburbs, to enjoy lower land prices. Thus, future land use patterns will depend, in part, on people's preferences for different conveniences; and this raises important policy questions about land prices, travel costs, and network congestion. Most existing studies using agent-based simulations to estimate SAV fleet-size impacts assume that a fixed number or share of person-trips are served by SAVs. In reality, SAV choice will depend greatly on many attributes, including cost. This work allows for estimation of an individual's SAV usage frequency at different price points ($1, $2 and $3 per trip-mile), resulting in more realistic simulations, across different pricing scenarios. Long-term land use changes from CAV technologies are also a major concern. Households that may move towards or away from the core are identified here, using models of home-location preference, once CAVs and SAVs become a common mode of transport.

CAVs have the potential to dramatically reduce the 90% of all crashes that result from driver error (NHTSA 2008). However, the travel-burden reductions provided by these technologies, along with empty-SAV travel (for passenger pick up and for fleet rebalancing, in time and space) are likely to deliver additional vehicle-miles traveled (VMT). Simultaneously, efficient on-demand ride-sharing systems may compensate for or offset some share of the increased VMT (Fagnant and Kockelman 2016). In addition, roadway operators and transportation agencies may need to adopt smart congestion-pricing strategies to counter the rising VMT. In the absence of methods to evaluate VMT's overall change, CAVs' safety impacts remain debatable[4] (Anderson et al. 2014). For similar reasons, Greenblatt and Shaheen (2015) estimated a very broad range (from an 80% decrease to a 300% increase) for energy use and greenhouse emission impact of CAVs. While the present study emphasizes the understanding of public opinions, and not estimating overall VMT changes, groups of individuals who will be supporting (or not supporting) different congestion pricing strategies (e.g., using toll revenues to reduce property taxes or distributing revenues uniformly to all travelers) are identified.

[3] The simulation-based approaches to forecast the adoption of any new technology generally allows population to evolve each year (see Bansal and Kockelman (2016) for the simulation-based forecast of CAV adoption in the next 30 years). To illustrate the importance of estimating the peer-pressure effect in the context of CAV adoption, consider the following example: if an individual is estimated to buy CAV technology when at least 50% of his/her relatives own that technology, then in the forecasting simulation if this situation occurs at particular year and individual's WTP is more than the price of that technology, then individual is allowed to buy that technology.

[4] Kockelman and Li (2016) provided valuation of CAVs' safety benefits, but did not account for an overall change in VMT.

In sum, this study's results reveal where many Americans currently stand on their WTP for CAV technologies, perceptions of CAVs' top 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 CAV technologies, and opinions about tolling policies. Though this study's primary objective is to draw behavioral insights, as detailed above, various model estimation results add realism for forecasting fleet evolution and SAV use rates. With the same exploratory objectives, multivariate associations between Texans' opinions about CAVs and their technology awareness, driving attitudes (e.g., support for speed governors on all new vehicles), and driving experiences (e.g., number of crashes and number of moving violations in recent years) are provided here. 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. Table 1 summarizes the key findings of the studies with summary statistics and simplistic analysis. Clark et al.'s (2016) recent report is a useful reference for review of such past studies. The past studies, which estimated econometric models to understand the public opinion about CAVs, are discussed in detail here.

Krueger et al. (2016) conducted a stated choice experiment on a sample of 435 Australian residents to understand their preferences for SAVs and ridesharing, via random-parameters logit choice model. In reference to a recent trip, respondents were asked to choose among three options: SAV without ridesharing, SAV with ridesharing, or no change in their chosen travel mode. Australian respondents reported shifting their travel model to SAVs for around 36% of trips. Model results indicate that younger travelers and current carsharing users are more likely to prefer SAVs with ridesharing. If the respondent had used public transport for his/her recent trip, mode switching was less likely. Both SAV options are estimated to be more attractive for work trips, but the SAV with ridesharing option was less likely for leisure trips. Those model parameters can be directly used in the frameworks of past studies (Burns et al. 2013; Fagnant et al. 2015) to estimate more realistic environmental impacts and optimal SAV fleet sizes.

Haboucha et al. (2015) investigated preferences for SAVs or privately-owned AVs for work- and education-related trips. They conducted stated choice experiments on a sample of 721 Israelis and Americans, using hybrid choice models in parameter estimation. 44% of respondents chose regular or conventional vehicles; and, even if SAVs were to be free for use, only 75% showed interest in using them. As compared to Americans, Israelis were estimated to have a higher likelihood of shifting toward SAVs. The researchers concluded that educating the public about SAVs' benefits and increasing the cost of regular car use are ways to encourage SAV usage. While Krueger et al. (2016) and Haboucha et al. (2015) estimated preference for SAVs over regular mode, this paper estimates the frequency of SAV usage at different price points.

Table 1 Review of past studies reporting summary statistics and simplistic analysis of the public opinion about CAVs

Authors	Sample size	Key findings
Accenture Research (2011)	2006 U.S. and British consumers	49% of consumers showed comfort in using Level 4 AVs. 48% of the remaining 51% consumers may be encouraged to use AVs if the driver can regain control
Casley et al. (2013)	450 participants from Worcester Polytechnic Institute	Public's biggest concern: safety; second biggest concern: legislation problems. Respondents' estimate of cost to add Level 4 automation[a] and WTP: US$5000 and $1000
Cisco Systems (2013)	1514 adults across 10 countries	57% of respondents would ride in a driverless car. Developing countries' citizens expressed higher trust on driverless cars than respondents from already developed countries
Continental (Sommer 2013)	1000 car users per country, across 7 countries	Most of the respondents would feel comfortable riding in AVs in light traffic and on freeway journeys. 74% Chinese and 50% Americans did not believe that AVs will function reliably
KPMG (2013)	Three focus groups in California, Illinois, and New Jersey	Contrary to Ipsos MORI (2014) and Schoettle and Sivak (2015), women were more receptive to the concept of an AV. Median WTP to add Level 4 automation on $30,000 car was $4500
Insurance.com (Vallet 2014)	2000 American drivers	22.4% were ready to ride in a Level 4 AV, and 24.5% reported never wanting to use AVs. A potential 80% discount on car insurance changed these numbers to 37.6 and 13.7%
Ipsos MORI (2014)	1001 Britons	Only 18% of respondents thought it was important for car manufacturers to focus on driverless technologies. Young men who live in urban areas showed more interest in AVs
Schoettle and Sivak (2014)	1533 adults from the UK, USA and Australia	More than half of the sample had generally positive opinion about the impacts of AVs. 57% respondents reported $0 WTP for full automation, with WTP of $1880 as the 75th percentile
Underwood (2014)	217 experts (with more than 80% holding master's degrees)	Main barriers for Level 4 AVs: legal issues and technological limitations. More than 25% of experts agree that AVs must be at least twice as safe as conventional vehicles. More than 75% of experts believe that a few AV crashes should be socially acceptable
Power (2015)	5300 new-car buyers	Younger generations have a higher preference for Level 3 and Level 4 automation, but Boomers and Pre-boomers were inclined towards Level 1 technologies
Kyriakidis et al. (2015)	4886 respondents (around the world)	The biggest concerns: information security (e.g., hacking) and legal liability. 22% reported $0 WTP to add full (Level 4) automation and only 5% would pay more than $30,000
NerdWallet (Danise 2015)	1028 Americans	44% of men and 23% women were concerned about losing fun of driving. 55% women and 37% men reported safety as the biggest concern. Only 6% will send their children alone to friend's house in AV. 21% reported WTP of more than $5000 to add Level 4 Automation
Schoettle and Sivak (2015)	505 U.S. motorists	Young men had a greater preference for partial or full automation over no automation. Surprisingly, there was a greater concern for riding in Level 4 AVs as compared to Level 3 AVs
Bansal and Kockelman (2016)	2167 Americans	WTP to add DSRC-based connectivity and Level 4 Automation: $67 and $5857. More than 50% of respondents reported $0 WTP to add connectivity and Level 4 Automation. 50% of respondents were uncomfortable in sharing vehicle-to-vehicle information

[a] NHTSA (2013) has defined different vehicle automation levels succinctly as follows: "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"

Howard and Dai (2013) surveyed 107 visitors of the Lawrence Hall of Science in Berkeley, California. They found that safety was the most attractive feature of AVs for visitors, while a lack of control over the vehicle was the least attractive feature. To estimate the multivariate relationship between public opinions and their demographics, they used logit and log-linear regression models. Higher-income individuals showed a higher likelihood of using SAVs and retrofitting their cars with AV technologies.

In another study, Bansal et al. (2016) 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 their least concern. Average WTP of Austinites to add Level 3 and Level 4 automation is \$3300 and \$7253, respectively. More than 80% of the respondents did not show interest in using SAVs at costs higher than current carsharing prices. Wealthier and tech-savvy males expressed a higher willingness to pay to add CAV technologies, but older licensed drivers expressed less interest in these technologies.

This study examines various public opinions, similar to Bansal et al.'s (2016) study, but on a larger and relatively unbiased sample[5] of 1088 respondents, with additional explanatory variables (e.g., crash history and opinion about safety regulations), and using different model specifications.[6] This study also estimates a few related preferences, such as adoption timing of CAV technologies' (dependence on relatives/friends) and home location shifting decisions (once AVs become a common mode of transport), which have not yet been pursued by other researchers.

Survey design, data cleaning, and geocoding

With funding from the Texas Department of Transportation, and a recent survey of Americans showing Texans to offer a balanced representation of U.S. responses (Bansal and Kockelman 2016), a Texas-wide survey, asking 93 questions distributed in seven 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. At the start of the survey, information about all levels of automation and relevant pictures showing technology in (virtual) use were provided to help respondents understand each technology's function and application. Respondents were asked about their opinions regarding AVs (e.g., concerns and benefits of AVs), crash history and opinions about speed regulations[7] (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

[5] This study conducted survey through a professional survey firm, but the data for Austin study were collected by distribution unpaid survey among Austin neighborhood association and also at social-networking websites. Though both studies calculated sample weights, but original sample is relatively unbiased for the current study as compared to the Austin study.

[6] Bansal et al. (2016) used ordered probit specification to estimate WTP of Level 3 and Level 4 Automation, but this study uses interval regression for the same.

[7] 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.

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.

A total of 1297 Texans completed the survey, but after eliminating the fast responses and going through various sanity checks,[8] 1088 Texans remained eligible for further analysis. Since, the sample over-represented and under-represented various demographic groups, person- and household-level weights were calculated to remove bias in 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 Texas.[9] 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).[10] The sample underrepresented women between the ages of 34 and 44 without high school diplomas and overrepresented men between the ages of 34 and 44 with bachelor's degrees. So those two demographic categories required the strongest reweighting, via factors of 4.53 and 0.63, respectively.

To understand the relationship between built-environment actors (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 an open-source census-tract-level shape file in ArcGIS. The internet protocol (IP) locations were used as proxies for the respondents who recorded an incorrect address or none at all. 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.

Summary statistics

Table 2 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 included in summary statistic calculation and model calibration to correct for sample biases.

[8] Respondents who completed the survey in less than 15 min 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.

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

[10] 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.

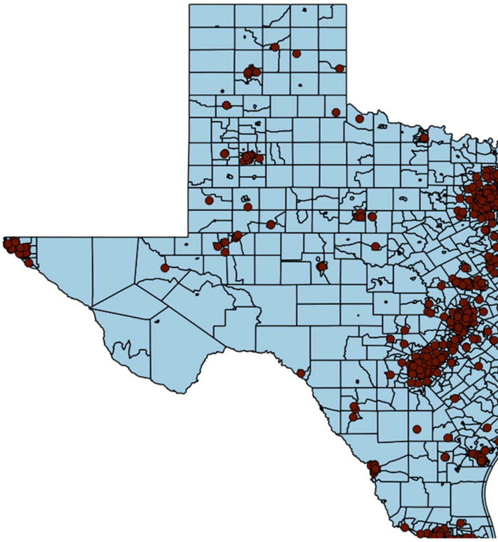

Fig. 1 Geocoded locations of respondents across Texas

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 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 their 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 the past 15 years. Each respondent received at least one moving violation within the last ten years, on average, while 20% received more than one violation. These statistics indicate that Texans appear to be average drivers in terms of safety precautions.

Key response variables

Table 3 shows respondents' opinions about and average WTP for different automation levels and connectivity.[11] Texans valued Level 2, Level 3, and Level 4 automation at

[11] 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). Vehicle to vehicle (V2V) and vehicle to infrastructure (V2I), both can be facilitated by DSRC.

Table 2 Population-weighted summary statistics of explanatory variables ($N_{obs} = 1088$)

Type	Explanatory variable	Mean	SD	Min.	Max.
Person-based predictors	Licensed driver (number of years)	19.11	12.50	0	32.5
	Licensed driver for more than 20 years	0.51	0.50	0	1
	Have U.S. driver license?	0.86	0.35	0	1
	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-based predictors	Household size over 3?	0.27	0.45	0	1
	Annual household income ($)	59,506	46,843	5000	225,000
	Annual household income is less than $30,000?	0.28	0.45	0	1
	Household size	2.62	1.43	1	9
	Number of workers in household	1.21	0.89	0	6
	More than one worker in household?	0.36	0.48	0	1
	Own at least one vehicle?	0.94	0.24	0	1
	Number of children in household	0.62	1.05	0	6
Location-based predictors	Distance between home and public transit stop (miles)	6.12	6.20	0.5	17.5
	Distance between home and city's downtown (miles)	9.59	5.97	0.5	17.5
	Home and city's downtown are more than 10 miles apart?	0.47	0.50	0	1
	Employed and over 16 years of age (per square mile)	2536	2619	0	20,384
	% of families below poverty line in the census tract	13.01	11.20	0	100
	Population density (per square mile)	3253	3366	1	32,880
Travel-based predictors	Drive alone for work trips?	0.51	0.50	0	1
	Number of personal business trips in past 7 days	1.58	2.26	0	9.5
	More than 2 personal business trips in past 7 days?	0.20	0.40	0	1
	Number of social (or recreational) trips in past 7 days	2.25	2.23	0	9.5
	More than 2 social (or recreational) trips in past 7 days?	0.31	0.46	0	1
	Annual VMT (miles)	8607	6391	1500	22,500
	Annual VMT is more than 15,000 miles?	0.17	0.38	0	1

Table 2 continued

Type	Explanatory variable	Mean	SD	Min.	Max.
Tech-based predictors	Carry a smartphone?	0.77	0.42	0	1
	Have heard about Google car?	0.59	0.49	0	1
	Familiar with UberX or Lyft?	0.64	0.48	0	1
	Have heard about CVs?	0.19	0.15	0	1
	Familiar with carsharing?	0.25	0.44	0	1
	Own at least a vehicle with Level 2 automation?	0.07	0.26	0	1
Safety-based predictors	Support the use of red light camera?	0.54	0.50	0	1
	Support the use of automated speed enforcement?	0.52	0.50	0	1
	Support the use of speed governors on all new vehicles?	0.48	0.50	0	1
	Number of fatal (or serious) crashes in past 15 years	0.28	1.43	0	16
	At least one fatal (or serious) crash in past 15 years	0.08	0.27	0	1
	Number of crashes with only monetary loss in past 15 years	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

\$2910, \$4607, and \$7589, on average; in contrast, 54.4, 31.7, and 26.6% of Texans are not willing to pay (WTP) more than \$1500 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 rates.[12]

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 may play a key role in boosting CV adoption rates (Sheldrick 2014).

Table 4 shows respondents' opinions about SAV adoption in different pricing scenarios[13] and home-location shifting decisions[14] when AVs and SAVs become common modes

12 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.

13 Before asking questions about the adoption rates of SAVs, respondents were given a definition for SAV and the following pricing information for current ridesharing and carsharing services: "Taxis in most U.S. cities presently cost about \$2.50 to \$3.50 per mile. UberX and Lyft (companies providing real time on-demand taxi service) charge about \$1.50 per mile. Car2Go (a company providing point-to-point carsharing service) charges \$0.80 to \$1.25 per mile within its Austin-area geofence and \$15 per hour of parking outside of this area".

14 Prior to asking respondents about their home-location shift decisions, they were provided with the following information: "Autonomous vehicles may make travel easier for many people, and some travelers may decide to live further from the city center, their workplaces, and their children's schools. Alternatively,

Table 3 WTP for and opinions about connectivity (1063)[a] and automation technologies ($N_{obs} = 755$)[b]

Response variable	Percentages	Mean	SD	Min.	Max.
WTP for adding connectivity		\$127	\$164	\$0	\$1100
\$0	29.3				
\$1 to \$99	28.1				
\$100 to \$199	20.4				
\$200 to \$299	11.2				
\$300 or more	11.0				
WTP for adding LV 4 automation		\$7589	\$7628	\$750	\$31,500
Less than \$1500	26.6				
\$1500 to \$5999	28.7				
\$6000 to \$11,999	13.6				
\$12,000 or more	31.1				
WTP for adding LV 3 automation		\$4607	\$5421	\$750	\$31,500
Less than \$1500	31.7				
\$1500 to \$2999	24.5				
\$3000 to \$5999	21.4				
\$6000 or more	22.4				
WTP for adding LV 2 automation		\$2910	\$4312	\$750	\$31,500
Less than \$1500	54.4				
\$1500 to \$2999	23.3				
\$3000 or more	22.3				
Adoption timing of Level 4 AVs					
Never	39				
When 50% friends adopt	32				
When 10% friends adopt	15				
As soon as available	14				
Interest in adding connectivity					
Not interested	26				
Neutral	35				
Interested	39				

All paper results are population weighted/sample corrected

[a] The questions about interest in and WTP for connectivity were only asked to those (1063 out of 1088 respondents) whose households have a vehicle or are planning to buy a vehicle in the next 5 years

[b] The questions about WTP for different automation levels were asked only of those (755 out of 1088 respondents) who are planning to buy a vehicle in the next 5 years

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%

Footnote 14 continued
households living in urban locations will be able to access a low cost (for example, \$1.50 per mile) shared fleet of autonomous vehicles. This will allow them to let go of vehicles they presently own, and turn to other transportation options (like walking, biking, and utilizing autonomous buses for some trips)".

Table 4 Opinions about SAV adoption rates, congestion pricing, and home location shifting ($N_{obs} = 1088$)

Response variable	Percentages
Adoption rates of SAVs at $1/mile	
Will not use	41.0
Less than once a month	17.5
Once a month	17.5
Once a week	16.7
Rely entirely	7.3
Adoption rates of SAVs at $2/mile	
Will not use	48.6
Less than once a month	19.8
Once a month	15.4
Once a week	11.6
Rely entirely	4.6
Adoption rates of SAVs at $3/mile	
Will not use	59.1
Less than once a month	17.2
Once a month	11.7
Once a week	8.1
Rely entirely	3.9
Toll congested highways if reduce property tax	
Definitely not support	25.1
Probably not support	11.5
Do not know	26.2
Probably support	22.6
Definitely support	14.7
Time-varying tolls on all congested roadways	
Definitely not support	22.8
Probably not support	11.3
Do not know	31.8
Probably support	24.6
Definitely support	9.5
Home location shift due to AVs and SAVs	
Move closer to city center	7.4
Stay at the same location	81.5
Move farther from city center	11.1
Toll congested highways if distribute revenues	
Definitely not support	26.6
Probably not support	14.2
Do not know	26.3
Probably support	21.4
Definitely support	11.5

All paper results are population weighted/sample corrected

indicated their intention to stay at their current locations. This finding is consistent with Bansal et al.'s (2016) Austin study, where 74% of Austinites expected to remain at their current home locations. It is interesting that Texans' support for different congestion pricing policies does 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.

Opinions about AVs and CVs

Table 5 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 the two most popular responses.[15] 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 an interest in using AVs for social or recreational trips.

Table 6 summarizes key concerns and benefits of AVs. Affordability and equipment failure are respondents' top two concerns regarding AVs; the two least concerning aspects are learning how to use AVs and, surprisingly, privacy breaches. Texans expect that implementation of AVs can lead to better fuel economy and crash reduction: 53.9 and 53.1% of the respondents, respectively, indicated that these benefits will be very significant.

Table 7 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. In-vehicle displays allowing one to compose emails and surf the Internet are the two least intriguing features: 58.1 and 51.5% of the respondents indicated no interest in these features. Most features offered in the survey are accompanied by less 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 are 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.

Opinions about carsharing and transportation network companies (TNCs)

Table 8 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%) indicated they had no desire 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 doing so. Lastly, only 16.4% of Texans reported being comfortable in sharing a ride with a complete stranger.

[15] Around 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.

Table 5 Opinions about level 4 self-driving technology (N_{obs} = 1088)

Response variable	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 in 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)[a]			
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

All paper results are population weighted/sample corrected

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

Table 6 Major concerns and benefits associated with AVs (N_{obs} = 1088)

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
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 significant (%)**	**Very significant (%)**
Fewer crashes	7.3	39.6	53.1
Less congestion	10.8	44.6	44.6
Lower emissions	11.7	42.5	45.7
Better fuel economy	7.7	38.4	53.9

All paper results are population weighted/sample corrected

Table 7 Current adoption and opinion about connectivity features and strategies

Adoption of connectivity feature (N_{obs} = 1063)[a]	Not interested (%)	Interested (%)	Already 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 accident	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} = 1088)	Do not support	No opinion	Support
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 (N_{obs} = 1088)	Average rank
Safety	1.36
Emissions (excluding greenhouse gas)	2.27
Travel times (and congestion)	2.64

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

[a] Questions about interest in connectivity features were asked only of those (1063 out of 1088 respondents) whose households have a vehicle or are planning to buy a vehicle in the next 5 years

Model estimation

This study estimated WTP to add connectivity and different levels of automation using an interval regression (IR) model.[16] Wooldridge (2013) provides many details about the IR

[16] Respondents were asked to choose WTP interval (e.g., \$1500 to \$2999 to add automation) and also provided with options of “\$3000 or more” and “\$1000 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.

Table 8 Opinions about carsharing and on-demand taxi services ($N_{obs} = 1088$)

Carsharing (Zipcar, Gar2Go)			
Have heard about carsharing	25.5%		
Among those who have heard about carsharing			
Member of Zipcar or Car2Go	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 Lyft)			
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 sharing 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 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%

All paper results are population weighted/sample corrected

model, which is briefly described here, for interval response values.[17] The key IR 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 density function and w_j is a population-corrected weight for the jth observation.

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

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 (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.

Four 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 on an SAV less than once a month", μ_2 is the threshold between "will rely on an SAV less than once a month" and "will rely on an SAV at least once a month", μ_3 is threshold between "will rely on an SAV at least once a month" and "will rely on an SAV at least once a week", and μ_4 is threshold between "will rely on an SAV at least once a week" and "will rely entirely on SAV fleet".

The adoption rate probabilities are as follows:

$$\Pr(\text{will never use SAVs}) = \Pr\left(y_i^* \leq \mu_1\right) \tag{4}$$

$$\Pr(\text{will rely on an SAV less than once a month}) = \Pr\left(\mu_1 \leq y_i^* \leq \mu_2\right), \tag{5}$$

$$\Pr(\text{will rely on an SAV atleast once a month}) = \Pr\left(\mu_2 \leq y_i^* \leq \mu_3\right), \tag{6}$$

$$\Pr(\text{will rely on an SAV atleast once a week}) = \Pr\left(\mu_3 \leq y_i^* \leq \mu_4\right), \tag{7}$$

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

In the first step of estimation, a subset of explanatory variables from Table 2 is included. In the subsequent steps, the covariates with the 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 0.05, those with p-values up to 0.32 were because such covariates may offer statistical significance in future studies. Finally, R^2 and adjusted R^2 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 shifted by 40% or more (i.e., to 1.4 or 0.6 of their original predictions).

Table 9 Interest in connectivity model results (using ordered probit)

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[a]	Coef.	Std. dev.			
Not interested vs. neutral	−0.356	0.282	–	–	–
Neutral vs. interested	1.368	0.285	–	–	–

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

[a] N_{obs}: 1063, McFadden's R^2: 0.082, McFadden's adjusted R^2: 0.070

Interest in and WTP to add connectivity

Tables 9 and 10 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 farther 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 10 WTP for connectivity model results (using interval regression)

Covariates[a]	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	–	–

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

[a] N_{obs}: 1063, McFadden's R^2: 0.038, McFadden's adjusted R^2: 0.034

WTP for automation technologies

Table 11 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) and appear WTP more for all levels of automation, on average. However, consistent with the findings of the *WTP for Connectivity* model results (Table 10) and findings in Bansal et al. (2016), 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 WTP 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 less WTP 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 especially WTP 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 11 WTP for automation technologies model results (using interval regression)

	Coef.	Std. coef.	Z-stat
Covariates (Model 1: WTP for Level 4 automation)[a]			
Intercept	10,300	–	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 ($)	1.04E−02	0.078	1.81
Single?	1000	0.064	1.63
Population density (per square mile)	−0.11	−0.046	−1.29
Sigma (σ)	6961	–	–
Covariates (Model 2: WTP for Level 3 automation)[b]			
Intercept	7179	–	7.17
Have heard about Google car?	1094	0.099	2.58
Support the use of speed governors on all new vehicles?	1229	0.114	3.27
Number of fatal (or serious) crashes in past 15 years	438.6	0.134	4.82
Familiar with UberX or Lyft?	−506.8	−0.041	−1.21
Licensed driver (number of years)	−54.56	−0.118	−1.52
Number of personal business trips in past 7 days	96.91	0.037	1.06
Distance between home and public transit stop (miles)	−42.49	−0.049	−1.26
Distance between home and city's downtown (miles)	40.98	0.045	1.22
Age of respondent (years)	−73.12	**−0.217**	−2.45
Household income ($)	7.53E−03	0.069	1.79
Sigma (σ)	4792	–	–
Covariates (Model 3: WTP for Level 2 automation)[c]			
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	–	–

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

[a] N_{obs}: 755, McFadden's R^2: 0.035, McFadden's adjusted R^2: 0.029

[b] N_{obs}: 755, McFadden's R^2: 0.044, McFadden's adjusted R^2: 0.039

[c] N_{obs}: 755, McFadden's R^2: 0.048, McFadden's adjusted R^2: 0.042

Table 12 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
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[a]	Coef.	Std. dev.				
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	–	–	–	–

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

[a] N_{obs}: 1088, McFadden's R^2: 0.059, McFadden's adjusted R^2: 0.046

Adoption timing of autonomous vehicles

Table 12 summarizes the OP model estimates of AV adoption timings (i.e., will never adopt an AV, will adopt AVs when 50% of friends adopt, will 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 11),[18] in that adoption timing of those who indicate higher WTP for AVs is estimated to depend less on their friends' adoption rates.

[18] 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.

SAV adoptions rates under different pricing scenarios

Table 13 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 11'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.[19]

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 violations.[20] 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 WTP 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.

Home location shifts due to AVs and SAVs

Table 14 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)[21] 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

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

[20] 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.

[21] 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.

Table 13 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[a]	Coef.	Std. dev.					
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	–	–	–	–	–
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**

Table 13 continued

Covariates (Model 2: $2 per mile)	Coef.	Z-stat	ΔPr_1	ΔPr_2	ΔPr_3	ΔPr_4	ΔPr_5
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[b]	Coef.	Std. dev.					
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	–	–	–	–	–
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

Table 13 continued

Covariates (Model 3: $3 per mile)	Coef.	Z-stat	ΔPr_1	ΔPr_2	ΔPr_3	ΔPr_4	ΔPr_5
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[c]	Coef.	Std. dev.					
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	–	–	–	–	–

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

[a] N_{obs}: 730, McFadden's R^2: 0.113, McFadden's adjusted R^2: 0.097

[b] N_{obs}: 730, McFadden's R^2: 0.123, McFadden's adjusted R^2: 0.108

[c] N_{obs}: 730, McFadden's R^2: 0.121, McFadden's adjusted R^2: 0.105

Table 14 Home location shifts due to AVs and SAVs model results (using ordered probit)

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[a]	Coef.	Std. dev.			
Shift closer vs. stay at the same location	−4.992	0.589	–	–	–
stay at the same location vs. shift farther	0.103	0.518	–	–	–

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

[a] N_{obs}: 1088, McFadden's R^2: 0.112, McFadden's adjusted R^2: 0.087

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 the higher density of low-cost SAVs near the 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.

Support for tolling policies

Table 15 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 policies.[22] In Policy 1, the revenue from a congested highway toll is used to reduce property taxes; in Policy 2, the revenue from a congested highway toll 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

[22] Safety- and tech-based predictors were not used in these models' specifications.

Table 15 Support for tolling policies model results (using ordered probit)

Covariates (Model 1: toll congested highways if reduce property tax)	Coef.	Z-stat	ΔPr_1 (%)	ΔPr_2 (%)	ΔPr_3 (%)	ΔPr_4 (%)	ΔPr_5 (%)
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[a]	Coef.	Std. dev.					
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	–	–	–	–	–
Covariates (Model 2: toll congested highways if distribute revenues)	Coef.	Z-stat	ΔPr_1 (%)	ΔPr_2 (%)	ΔPr_3 (%)	ΔPr_4 (%)	ΔPr_5 (%)
Licensed driver (number of years)	−0.043	−5.74	**62.6**	15.2	−8.7	−36.7	**−63.6**
Distance between home and public transit stop (miles)	−0.051	−4.00	36.9	10.8	−4.0	−23.1	**−45.2**
Distance between home and city's downtown (miles)	0.026	1.83	−15.9	−6.8	0.2	11.5	31.1
Annual VMT (miles)	2.63E−05	2.00	−16.7	−7.2	0.1	12.1	33.1
White, European white or Caucasian?	−0.460	−2.93	24.8	7.9	−2.2	−16.1	−33.5
Number of children in household	0.160	2.05	−17.0	−7.3	0.1	12.3	33.7
Bachelor's degree holder	0.227	1.50	−11.5	−4.7	0.2	8.2	21.5
Full time worker?	0.307	1.89	−15.2	−6.4	0.2	10.9	29.5

Table 15 continued

Thresholds[b]	Coef.	Std. dev.					
Definitely not support vs. probably not support	−1.780	0.280	–	–	–	–	–
Probably not support vs. do not know	−1.086	0.272	–	–	–	–	–
Do not know vs. probably support	0.027	0.272	–	–	–	–	–
Probably support vs. definitely support	1.596	0.251	–	–	–	–	–
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[c]	**Coef.**	**Std. dev.**					
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	–	–	–	–	–

Table 15 continued

Thresholds[c]	Coef.	Std. dev.					
Probably support vs. definitely support	1.185	0.539	–	–	–	–	–

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

[a] N_{obs}: 1088, McFadden's R^2: 0.049, McFadden's adjusted R^2: 0.041

[b] N_{obs}: 1088, McFadden's R^2: 0.061, McFadden's adjusted R^2: 0.054

[c] N_{obs}: 1088, McFadden's R^2: 0.057, McFadden's adjusted R^2: 0.048

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 payers,[23] 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.

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. Table 16 reveals some consistent relationships (positive or negative) between explanatory variables and key response variables (like respondents' WTP for DSRC-based connectivity and AVs, their expected SAV use rates at \$1, \$2 and \$3 per mile, and likely adoption timing of AVs). Older and more experienced drivers expressed lower WTP for connectivity and all automation levels, whereas higher-income and more safety-cautious persons (e.g., those supportive of speed governors on vehicles and/or having experienced a fatal crash) are WTP more to add these technologies. More experienced drivers may trust their driving skills more than those of a computer, and older individuals may find it difficult to visualize the emergence of reliable self-driving cars in their lifetimes. Caucasian licensed drivers who live further from transit stops appear less likely to use SAVs, while safety-cautious individuals, those who live more than 10 miles away from the downtown, and those in households with more workers appear more likely to be the frequent SAV users, under all pricing scenarios, everything else constant. Finally, those in households already possessing a Level 2 vehicle and living farther from city center appear more ready to shift their homes closer to the city center, in order to enjoy higher frequency SAV service (or whatever else they associate with this pending transportation transformation).

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 \$2910, \$4607, \$7589, 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 top two AV-related concerns. People expect that AVs will help provide better fuel economy and decrease crashes: 53.9 and 53.1% of the respondents, respectively, indicated that these benefits will be very significant.

In sum, the contribution of this study is threefold: first, a detailed set of summary statistics (arguably the most comprehensive to date) shed much light on current public perceptions of CAVs and SAVs. Second, knowledge of practically significant explanatory variables can allow policymakers to identify the regions with both low and high penetration rates for future CAV technologies. Awareness campaigns may be valuable for low-penetration locations and

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

Table 16 Summary of predictive model relationships

Explanatory variable	WTP for CV	WTP for L4	WTP for L3	WTP for L2	SAV use at \$1	SAV use at \$2	SAV use at \$3	Faster adoption of AVs
Licensed driver (number of years)	−−−	−	−	−		−	−	
Have U.S. driver license?					−			
Age of respondent (years)	−	−−−	−−−	−−−				−−−
Older than 54 years?						−		
Ethnicity: White, European white or Caucasian?	−			−	−−−	−	−	−
Marital status: married?						−	−	
No disability?	−						−	−
Bachelor's degree holder?	+							+
Employment: unemployed?					+			
Household size over 3?				−			+	
Household income (\$)	+	+	+	+				
Household income is less than \$30,000?					+			
Household size	−							−
Number of workers in household					+	+	+	
More than one worker in household?								+
Distance between home and public transit stop (miles)		−	−		−−−	−	−	−−−
Distance between home and city's downtown (miles)			+		+	+	+	
Population density (per square mile)		−						−−−
Number of social (or recreational) trips in past 7 days							+	
More than 2 social (or recreational) trips in past 7 days?						+		
Annual VMT (miles)	+	+						+
Annual VMT is more than 15,000 miles?					+			
Have heard about Google car?		+	+	+				
Familiar with UberX or Lyft?	+		−	−		−	−	
Have heard about CVs?		+				+	+	+
Support the use of automated speed enforcement?					+	+	+	+++
Support the use of speed governors on all new vehicles?	+	+	+	+	+++	+++	+++	+
Number of fatal (or serious) crashes in past 15 years	+		+	+++		+++	+++	

Table 16 continued

Explanatory variable	WTP for CV	WTP for L4	WTP for L3	WTP for L2	SAV use at \$1	SAV use at \$2	SAV use at \$3	Faster adoption of AVs
At least one fatal (or serious) crash in past 15 years					+			
Number of crashes with only monetary loss in past 15 years	+							
Number of moving violations in past 10 years	+				+	+		

All practically significant predictors with positive and negative marginal effects are denoted by +++ and −−−, respectively

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). Third, as detailed in the Introduction, this paper's model specifications can be instrumental in delivering more realistic forecasts of long-term CAV-technology adoption and quantifying system-level impacts of SAVs, as well as evolving travel demands and VMT.[24] More reliable forecasts may help auto manufacturers and investors select the ideal automation technologies for research and production, and help emerging SAV-fleet operators select prices and fleet size, and help planners, engineers and policymakers make 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).

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 an early stage in understanding CAV technologies, so their 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.

Acknowledgements

The authors thank three anonymous reviewers whose comments helped in significantly improving this paper. They are also obliged to Scott Schauer-West for his editing and admin support.

[24] 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 trip-making. In other words, long-distance trip-making frequencies are predicted to more than double, following access to AVs.

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