

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

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26 **ABSTRACT**

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

35
36 This study estimates the impact of demographics, built-environment variables, and travel
37 characteristics on Austinites' WTP for adding such automations and connectivity to their current
38 and coming vehicles. It also estimates adoption rates of shared autonomous vehicles (SAVs)
39 under different pricing scenarios (\$1, \$2, and \$3 per mile), choice dependence on friends' and
40 neighbors' adoption rates, and home-location decisions after AVs and SAVs become a common
41 mode of transport. Higher-income, technology-savvy males, living in urban areas, and those who
42 have experienced more crashes have a greater interest in and higher WTP for the new
43 technologies, with less dependence on others' adoption rates. Such behavioral models are useful
44 to simulate long-term adoption of CAV technologies under different vehicle pricing and
45 demographic scenarios. These results can be used to develop smarter transportation systems for
46 more efficient and sustainable travel.

1
2 **Keywords:** Connected and Autonomous Vehicles; Shared Autonomous Vehicles; Willingness to
3 Pay; Ordered Probit Models.
4

5 6 **1. INTRODUCTION AND MOTIVATION** 7

8 Car travel is relatively unsafe, costly, and burdensome. Roughly 2.2 million Americans are
9 injured in crashes each year, resulting in over 30,000 fatalities (NHTSA 2014b). The economic
10 cost of these crashes is roughly \$300 billion, which is approximately three times the U.S.'s
11 annual congestion costs (Cambridge Systematics 2011). Connected-autonomous vehicles
12 (CAVs) provide a solution to the burden of car travel, and have the potential to reduce a high
13 proportion of the 90% of crashes that result from driver error (NHTSA 2008). CAVs are the
14 biggest technological advances in personal transport that the world has seen in over a century,
15 with a promising future of safer and more convenient transportation.
16

17 CAVs are no longer a fantasy, and may soon become a daily mode of transport for hundreds of
18 millions of people. Several mainstream companies such as Google, Toyota, Nissan, and Audi are
19 developing and testing their own prototypes (Smiechowski 2014). With rapid advances in vehicle
20 automation and connectivity, the U.S. National Highway Traffic Safety Administration (NHTSA
21 2013 & 2014a) has recognized key policy needs for CAVs. California, Nevada, Florida, and
22 Michigan states have legislation to allow AV testing on public roads (Schoettle and Sivak 2014a).
23 Navigant Research (2014) estimated that 75% of all light-duty-vehicle sales around the globe
24 (almost 100 million annually) will be autonomous-capable by 2035. In accordance with this
25 timeline, Litman (2014) expects that AVs' beneficial impacts on safety and congestion are likely
26 to appear between 2040 and 2060. If AVs prove to be very beneficial, Litman (2014) suggests that
27 human driving may be restricted after the 2060.
28

29 Successful implementation of CAV technologies will require public acceptance and adoption of
30 these technologies over time, via CAV purchase, rental, and use (Heide and Henning 2006).
31 In the past three years, many researchers (Kyriakidis et al. 2014, Schoettle and Sivak 2014a &
32 2014b, Underwood 2014) and consulting firms (J.D. Power. 2012, KPMG 2013, and Continental
33 2015) have conducted surveys and focus groups to understand the public perception about
34 CAV's benefits and limitations. These studies provide descriptive statistics regarding public
35 awareness, concerns, and expected benefits of smart-vehicle technologies, but they do not
36 indicate how an individual's attributes (e.g., age, income, and education) and built-environment
37 factors (e.g., employment density, population density, and area type) affect their opinions and
38 willingness to pay (WTP) for such technologies.
39

40 This study designed and disseminated a survey for adult residents of Austin, Texas and received
41 358 completed responses. Those data facilitate a variety of perception and attitude analyses,
42 using various econometric models. Response variables include respondents' WTP for Level 3
43 AVs, Level 4 AVs, and CVs; adoption rates of shared AVs under different pricing scenarios;
44 adoption timing of CAV technologies; and home location decisions after AVs become a common
45 travel mode. Motivations for each behavioral model are provided below.
46

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

5
6 While AVs are set to emerge on the public market, they may quickly offer another mode of
7 transportation: shared autonomous vehicles (SAVs). SAVs offer short-term, on-demand rentals
8 with self-driving capabilities, like a driverless taxi (Kornhauser et al. 2013, Fagnant et al. 2015).
9 SAVs may overcome the limitations of current carsharing programs, such as vehicle availability,
10 because travelers will have the flexibility to call a distant SAV. Several studies (e.g., Burns et al.
11 2013, and Fagnant and Kockelman 2014) have shown how SAVs may reduce average trip costs
12 by 30% to 85%, depending on the cost of automation and expected returns on the fleet operator's
13 investment. Fagnant and Kockelman's (2015) agent-based simulation concluded that dynamic
14 ridesharing (DRS) has the potential to further reduce total service times (wait times plus in-
15 vehicle travel times) and travel costs for SAV users, even after incorporating extra passenger
16 pick-ups, drop-offs, and non-direct routings. Chen et al. (2015) extended some of that work, and
17 examined the performance (including profitability) of a fleet of shared electric AVs, across a
18 100-mile by 100-mile region. Pivoting off those simulations, this study explores the factors
19 affecting SAV adoption rates under three pricing scenarios: \$1, \$2, and \$3 per occupied-mile
20 traveled.

21
22 After AV adoption by neighbors and friends, individuals may gain confidence in such vehicles
23 and/or sense social pressures, prompting them to purchase such technologies. Thus, this study
24 estimates the adoption timing of AVs (e.g., will the respondent "never adopt" an AV, wait until
25 50% of his/her friends adopt an AV, or just 10% of his/her friends adopt one, or try to obtain an
26 AV as soon as such vehicles are available in the market).

27
28 More efficient use of travel time (by allowing work or cell-phone conversations, for example)
29 while riding in AVs may encourage individuals to shift their home locations to more remote
30 locations, to enjoy lower land prices (and thereby bigger homes or parcels). Thus, AVs can
31 exacerbate urban sprawl and increase a region's vehicle-miles traveled (VMT). However, a high-
32 density of low-cost SAVs in downtown areas may counteract such trends. Given the major land
33 use shifts that could occur, this study also explores the factors associated with residential shifts,
34 as motivated by AV and SAV access. The following sections describe related studies, survey's
35 design, many summary statistics, choice model specifications, key findings, and study
36 conclusions.

37 38 **2. LITERATURE REVIEW**

39
40 This section summarizes the key findings of recent public opinion surveys about adoption of
41 CAVs. Kyriakidis et al. (2014) conducted a survey of 5,000 respondents across 109 countries by
42 means of a crowd-sourcing internet survey. Results indicate that respondents with higher VMT
43 and who use the automatic cruise control feature in their current vehicles are likely to pay more
44 for fully-automated vehicles. Approximately 20% of respondents showed a WTP of more than
45 \$7,000 for Level 4 AVs, and approximately the same proportion of respondents did not want to

1 pay more to add this technology to their vehicle. Most importantly, 69% of respondents expected
2 that fully-automated vehicles are likely to gain 50% market share by 2050.

3
4 Schoettle and Sivak (2014a) surveyed 1,533 respondents across the U.K., the U.S., and Australia
5 to understand their perception about AVs. Results indicate that approximately two-thirds of
6 respondents had previously heard about AVs. Interestingly, 25% respondents were willing to
7 spend at least \$2,000 to add full self-driving automation in the US, while same proportion of
8 respondents in the UK and Australia were willing to spend \$1,710 and \$2,350, respectively.
9 However, 54.5% respondents in the U.S., 55.2% in the U.K., and 55.2% in Australia did not want
10 to pay more to add these technologies. When asked about their activities (e.g., work, read, and
11 talk with friends) while riding in Level 4 AVs, highest proportion, 41%, of respondents said they
12 would watch the road even though they would not be driving. Results of one-way analysis of
13 variance indicated that females are more concerned about AV technologies than males.

14
15 Underwood (2014) conducted a survey of 217 experts. Eighty percent of respondents had a
16 master's degree, 40% were AV experts, and 33% were CV experts. According to these experts,
17 legal liability is the most difficult barrier to fielding Level 5 AVs (full automation without
18 steering wheel), and consumer acceptance is the least. Approximately 72% of the experts
19 suggested that AVs should be at least twice as safe as the conventional vehicles before they are
20 authorized for public use. Fifty-five percent of the experts indicated that Level 3 AVs are not
21 practical because drivers could become complacent with automated operations and may not take
22 required actions.

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

30
31 A KPMG (2013) focus group study, using 32 participants, notes that respondents became more
32 interested in AVs when they were provided incentives like a designated lane for AVs, and
33 learned their commute time would be cut in half. In contrast to Schoettle and Sivak's (2014a)
34 findings, the focus group's discussion and participants' ratings for AV technology suggests that
35 females are more interested in these technologies than males. Continental (2015) surveyed 1,800
36 and 2,300 respondents in Germany and the United States, respectively. Approximately 60% of
37 respondents expected to use AVs in stressful driving situations, 50% believed that AVs can
38 prevent accidents, and roughly the same number indicated they would likely engage in other
39 activities while riding in AVs.

40
41 Recently, Schoettle and Sivak (2014b) surveyed 1,596 respondents across the U.K, the U.S., and
42 Australia to understand their perception about CVs. Surprisingly, only 25% of respondents had
43 heard about CVs. When asked about the expected benefits of CVs, the highest proportion,
44 85.9%, of respondents expected fewer accidents and the lowest proportion, 61.2%, expected less
45 distraction for the driver. Interestingly, 25% respondents were willing to spend at least \$500,
46 \$455, and \$394 in the U.S., the U.K, and Australia, respectively, to add CV technology.

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

3
4 As mentioned above, these past studies reveal important information about individual
5 perceptions of CAV technologies, but none has explored various related aspects, such as
6 adoption rates of SAVs under various pricing scenarios, home-location choices when SAVs and
7 AVs become common modes of transport, and peer-pressure effects on the adoption time of
8 AVs. Moreover, econometric analysis is missing in all of these studies, but is crucial for
9 devising efficient policies to increase market penetration of emerging transportation
10 technologies. This study explores statistical and practical significance of relationships between
11 respondents' demographics and built-environmental attributes, and their WTP for CAVs,
12 adoption rates of SAVs, residence-shift decisions, and adoption timing of AVs using univariate
13 and bivariate ordered probit (OP) models. These behavioral models will be very useful in
14 forecasting adoption of CAV technology and land use changes under different pricing scenarios.

15 **3. SURVEY DESIGN AND DATA PROCESSING**

16
17 The data were collected via a survey in Austin, Texas from October to December 2014 using
18 "Qualtrics", a web-based survey tool. Exploring respondents' preferences for adoption of
19 emerging vehicle and transport technologies, the survey asked 52 questions regarding
20 respondents' perceptions of AV technology upsides and downsides, ridesharing, and carsharing.
21 Respondents were also asked about their WTP for CAVs, adoption rates of SAVs in different
22 pricing scenarios, future home-location decisions, adoption timing of AVs, current travel
23 patterns, and demographics.

24
25 Austin neighborhood associations were first contacted via email and passed the survey requests
26 to their respective residents. A total of 510 respondents initiated the survey; only 358 of them
27 completed it. However, 11 of those were not Austinites and so were excluded from the sample,
28 resulting in a total sample of 347 adults (over 18 years of age). The sample over-represented
29 women, middle-aged persons (25-44 years old) and those with a bachelor's degree or higher.
30 Therefore, the survey sample proportions in each demographic class were scaled using the 2013
31 American Community Survey's Public Use Microdata Sample (PUMS 2013) for the Austin. The
32 population weights were calculated by dividing the sample into 72 categories based on gender,
33 age, education and household income. To understand the impact of built-environment factors
34 (e.g., employment density, population density, and area type) on preferences, respondents' home
35 addresses were geocoded¹ using Google Maps API and spatially joined with Austin's traffic
36 analysis zones (TAZs) using open source Quantum GIS.

37 38 **4. DATA SET STATISTICS**

39
40 Table 1 summarizes the demographic, built-environment, zone-level², and technology-related
41 variables after correction for biased-sample's demographics. This study uses these variables as

¹ For respondents, who did not provide their street address or recorded incorrect addresses, their internet protocol (IP) locations were used as the proxies for their home locations.

² The TAZ-level variables were obtained by spatial mapping of respondents' home locations with a TAZ-level shape files, obtained from Austin's Capital Area Metropolitan Planning Organization.

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

3
 4 **4.1 Current Technology Awareness**

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

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

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

14
 15 **4.2 Key Response Variables**

16 Table 2 summarizes the key response variables estimated in this study. At cost of more than
 17 \$5,000, 24% and 57% of respondents were willing to add Level 3 and Level 4, respectively, to
 18 their next vehicle purchase. As expected, the average WTP (of the population-corrected sample)

1 for Level 4 automation (\$7,253) is much higher than that for Level 3 automation (\$3,300).
 2 Apparently, AVs may not impact residential land-use patterns much, since 74% of respondents
 3 expect to stay at their current location even after AVs and SAVs become common modes of
 4 transport³. 30% showed interest in using AVs as soon as they are available for mass market sales
 5 in the U.S. Interestingly, approximately half of the respondents would prefer their family,
 6 friends, or neighbors to use AVs prior to their adoption. Only 15% and 3% of respondents
 7 expected to use SAVs once a week at a cost of \$2 per mile and \$3 per mile, respectively⁴.
 8 Responses like these imply that most respondents are not willing to spend more for SAV use than
 9 what UberX & Lyft charge (about \$1.50 per mile). However, with social acceptance of AVs and
 10 the reliability of SAVs for longer-distance trips, future SAVs costs may fall. At a cost of \$1 per
 11 mile, 41% of respondents expected to use SAVs at least once a week. Only 26% of respondents
 12 rejected a proposal of adding connectivity⁵ to their vehicles at a cost of less than \$100.
 13

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

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

15

16 **4.3 Other Opinions about AVs and CVs**

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

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

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

1 Table 3 summarizes the individuals' perceptions about the benefits and concerns of CAVs. 19%
 2 of respondents were not at all interested in owning Level 4 AVs. Respondents indicated three
 3 main issues regarding AVs: 50% of respondents were concerned about equipment or system
 4 failure, while 48% and 38% were concerned about interactions with conventional vehicles and
 5 affordability, respectively. Only 7% of respondents were apprehensive about learning to use
 6 AVs. 31% of respondents believe that AVs cannot help with calming congestion, making this the
 7 "least likely" AV benefit (among plausible options tested). When asked about the other three
 8 benefits (fewer crashes, lower emission, and better fuel economy), respondents considered them
 9 almost equally likely, but a reduction in crashes received maximum (63%) support. 75% of
 10 respondents indicated wanting to talk or text with friends and look out of the window while
 11 riding in AVs – making these the two most appealing tasks for respondents while traveling in
 12 Level 4 AVs. More than 70% of respondents would like to ride in AVs on freeways, high-speed
 13 highways, and congested traffic, while only 46 % would let the vehicles drive themselves on city
 14 streets. Surprisingly, only 47% of respondents have heard about CVs. It is worth noting that only
 15 4.3% of respondents are currently surfing internet and 6.2% are emailing while driving
 16 (conventional vehicles), but 31.7% and 39% are interested in adding these technologies to their
 17 vehicles, respectively.

18
 19 **Table 3:** Population-weighted Results for Opinion-based Questions on AVs and CVs (N_{obs}=347)

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

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

5. MODEL ESTIMATION

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

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

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

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

$$\Pr(\text{not interested}) = \Pr(y_i^* \leq \mu_1) \quad (2)$$

$$\Pr(\text{neutral}) = \Pr(\mu_1 \leq y_i^* \leq \mu_2) \quad (3)$$

$$\Pr(\text{interested}) = \Pr(y_i^* \geq \mu_2) \quad (4)$$

The WTP for AVs (Level 3 and Level 4) had two related response variables and so were jointly estimated using seemingly unrelated specifications⁶ of the bivariate OP model⁷ (as described in Sajaia [2008]).

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

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

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

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

5
 6 Practical significance is generally more meaningful than statistical significance. This study
 7 considers an explanatory variable to be practically significant if a one-standard-deviation
 8 increment in it leads to a significant shift in the response variable. In this paper, response
 9 variables are probabilities of ordered choice options, so an explanatory variable is considered to
 10 be practically significant if the predicted probabilities (i.e., the ΔPr_i shown in Tables 4 through 8)
 11 change by more than a factor of 1.3 or less than a factor of 0.7. In other words, there is at least 30
 12 percent shift in the predicted probability (which could be from 0.50 to 0.67 or to 0.35). If the
 13 shift in the model-predicted probability exceeds 50 percent (i.e., the ratio of the two is more than
 14 1.5 or less than 0.50), the explanatory variable is defined here as *highly* practically significant.
 15 McFadden's R-Square⁸ and adjusted R-square are also provided, to characterize all models'
 16 goodness of fit.

17 **5.1 Willingness to Pay for AVs**

18
 19 Table 4 summarizes the bivariate OP model estimates of WTP for adding Level 4 automation (of
 20 less than \$2,000, \$2,000 to \$5,000, \$5,000 to \$10,000, or more than \$10,000) and WTP for Level
 21 3 automation (less than \$2,000, \$2,000 to \$5,000, or more than \$5,000). Results indicate that
 22 male respondents with a greater number of children, living in higher- income neighborhoods, and
 23 who drive alone for social trips, ceteris paribus, are willing to pay more to add Level 3 and Level
 24 4 automation to their next vehicle. In contrast, licensed drivers living in more jobs-sense
 25 neighborhoods, and who are familiar with carsharing and ridesharing companies are estimated to
 26 pay less to add Level 3 and Level 4 automation to their next vehicles, ceteris paribus⁹. Perhaps
 27 individuals who are familiar with carsharing and ridesharing would rather rely on low-cost SAVs
 28 instead of buying a new vehicle with added automation technology. Interestingly, individuals
 29 who travel more (exhibit higher annual VMT) and who live farther from their workplace exhibit
 30 higher WTP for adding Level 4 AVs, but lower WTP for Level 3 AVs. Perhaps the opposite
 31 signs, but practical significance of both attributes for the WTP of Level 3 and Level 4 AVs
 32 reflect the individuals' perception that they would be able to use their travel time (for work,
 33 sleep, or other meaningful activities) in a Level 4 AVs, but not in Level 3 AVs.

34
 35 **Table 4:** Willingness to Pay for Autonomous Vehicles (Bivariate Ordered Probit Model Results)

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

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

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

Drive alone for work trips (1=yes)	0.616	1.72	-28.8%	-6.2%	7.5%	31.1%
Drive alone for social trips (1=yes)	0.833	2.28	-25.6%	-8.0%	8.6%	28.1%
Log(Annual VMT)	0.329	1.39	-20.2%	-15.7%	7.5%	32.7%
Distance from workplace (miles)	0.087	2.96	-22.3%	-13.9%	16.6%	27.3%
Gender (1=male)	0.442	1.28	-18.2%	-4.0%	5.7%	21.6%
U.S. driver license (1=yes)	-1.159	-1.36	18.3%	1.6%	-6.8%	-18.0%
Number of children	0.341	1.66	-15.5%	-16.4%	7.6%	21.7%
Age	-0.039	-4.02	53.5%	-12.4%	-21.5%	-45.0%
Total employment density (per mi ²)	-3.37E-04	-1.83	21.9%	3.7%	-8.2%	-21.2%
Median household income (\$ per year)	7.29E-06	1.95	-23.8%	-15.8%	7.2%	34.2%
Thresholds	Coef.	Std. Dev.				
<\$2,000 vs. \$2,000 to \$5,000	-7.401	0.386	--	--	--	--
\$2,000-\$5,000 vs. \$5,000-\$10,000	-6.514	0.299	--	--	--	--
\$5,000-\$10,000 vs. >\$10,000	-5.503	0.447	--	--	--	--
Covariates (WTP for Level 3)						
	Coef.	Z-stat	ΔPr₁	ΔPr₂	ΔPr₃	
Number of past crash experiences	0.217	1.59	-24.1%	11.0%	32.4%	
Carry smartphone (1=yes)	0.708	1.18	-10.5%	5.3%	16.5%	
Familiar with carsharing (1=yes)	-1.631	-1.37	20.1%	-15.9%	-20.1%	
Familiar with UberX or Lyft (1=yes)	-1.203	-1.49	19.9%	-10.8%	-25.8%	
Drive alone for work trips (1=yes)	0.539	1.46	-31.4%	28.1%	26.3%	
Drive alone for social trips (1=yes)	1.102	3.08	-15.9%	18.4%	12.9%	
Log(Annual VMT)	-0.470	-1.75	25.6%	-15.8%	-33.1%	
Distance from workplace (miles)	-0.085	-2.83	22.8%	-14.5%	-27.4%	
Gender (1=male)	0.507	1.48	-14.4%	5.8%	25.4%	
U.S. driver license (1=yes)	-1.623	-1.77	16.3%	-8.6%	-24.8%	
Number of children	0.485	2.32	-20.3%	8.9%	27.4%	
Age	-0.031	-2.53	35.6%	-26.4%	-37.3%	
Total employment density (per mi ²)	-2.30E-05	-2.11	16.2%	-8.6%	-24.7%	
Median household income (\$ per year)	8.26E-06	1.79	-18.9%	7.2%	32.2%	
Thresholds	Coef.	Std. Dev.				
<\$2,000 vs. \$2,000 to \$5,000	-8.865	0.488	--	--	--	
\$2,000-\$5,000 vs. >\$5,000	-7.323	0.373	--	--	--	
Correlation coefficient: 0.921 McFadden's R-Square: 0.101 McFadden's adjusted R-Square: 0.061						

1 Notes: N_{obs}=347. “Log (Annual VMT)” was used as an explanatory variable in the model, but corresponding ΔPr’s
2 were calculated with respect to “Annual VMT”. All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly
3 statistically significant predictors. All ΔPr’s with |ΔPr_i| > 30% are in **bold**, and indicate practically significant
4 predictors.
5

6 In addition, everything else equal, older persons are predicted to have a significantly lower WTP
7 for AVs (in a practically and statistically significant sense). Perhaps they are concerned about
8 learning to use AVs and do not trust these technologies. Practically significant and positive
9 associations between the number of crashes experienced by an individual and their WTP for AVs
10 indicates that such persons may be anticipating the safety benefits of AVs¹⁰. Respondents driving
11 alone for work trips are estimated to have a (practically and statistically) significantly higher
12 WTP for AVs, indicating the possibility of shifting commuters to SAV fleets in the future. A
13 high correlation coefficient estimate across these two OP equations ($\rho = +0.921$) strongly
14 supports the use of a seemingly unrelated bivariate OP specification here.

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

5.2 SAV Adoption Rates under Different Pricing Scenarios

Table 5 shows the OP model estimates of SAVs' adoption rates (i.e., relying on it less than once a month, at least once a month, at least once a week, or entirely on SAV fleet) in three pricing scenarios (\$1 per mile [Model 1], \$2 per mile [Model 2], and \$3 per mile [Model 3]). Results indicate that full-time male workers living in urban areas, ceteris paribus, are likely to use SAVs more frequently, but consistent with the findings of the WTP for AVs' model, licensed drivers are estimated to use SAVs less frequently under all three pricing scenarios (everything else constant). Perhaps many licensed drivers are concerned about losing the excitement of driving after AVs become a common mode of transport¹¹. Or they may have a hard time envisioning life without a privately held vehicle, and becoming largely reliant on SAVs. The practically significant positive associations of indicator variables (whether an individual has heard about Google's self-driving car and if an individual thinks that ABS is form of automation), in all three pricing-scenarios, suggests that tech-savvy individuals are likely to be frequent SAV users. Similarly, those living in denser neighborhoods expect higher SAV adoption rates (in all three models), perhaps due to less convenient parking facilities and lower vehicle ownership rates in these areas (Celsor and Millard-Ball 2007).

A highly practically significant and positive relationship between the home-distance from one's workplace and SAV adoption rates in Models 1 and 2 suggests that these workers are likely to use SAVs more often at current carsharing and ridesharing prices. Although this variable (respondents' distances from their workplace) does not appear in Model 3's final specification, another covariate, distance from downtown, may be capturing its effect¹². The individuals living farther from downtown, all other attributes remaining constant, are expected to use SAVs less frequently at \$3 per mile. Consistent with findings of the WTP for AVs' model, older persons are predicted to use SAVs less frequently, but individuals who have experienced more crashes in the past, ceteris paribus, have a practically significant inclination to use SAVs more frequently, even at \$2 and \$3 per mile (more than what carsharing companies and UberX or Lyft charge). The practical significance and negative association of the familiarity-with-carsharing indicator with SAV adoption rates in Models 2 and 3 suggests that individuals who already know carsharing's current price, may not be willing to pay more to use comparably convenient SAVs. A highly practically significant and negative relationship of an individual's annual VMT with SAV adoption rate (found only in Model 3) is as expected because SAVs at \$3 per mile may lead to a high annual travel cost for these individuals.

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

Covariates (Model 1: \$1 per mile)	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄
Have heard about Google car (1=yes)	1.835	2.91	-32.6%	-15.5%	26.1%	58.1%
ABS form of automation (1=yes)	0.903	2.54	-37.9%	-9.8%	39.9%	29.6%
Distance from workplace (miles)	0.126	4.20	-49.6%	-2.5%	36.6%	63.7%
Gender (1=male)	0.325	1.12	-10.6%	-3.0%	7.9%	18.2%
U.S. driver license (1=yes)	-1.267	-1.85	15.6%	2.7%	-11.9%	-20.9%
Number of children	-0.194	-1.25	12.4%	2.3%	-9.5%	-15.5%

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

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

Employment status (1=full-time worker)	0.403	1.10	-11.3%	-3.2%	8.5%	20.5%
Area type (1=urban)	0.493	1.15	-13.0%	-3.8%	9.7%	15.6%
Population density (per mi ²)	2.59E-04	2.20	-44.4%	-12.4%	32.3%	66.8%
Households density (per mi ²)	-5.67E-04	-2.11	25.2%	-11.9%	-11.1%	-24.2%
Basic employment density (per mi ²)	-2.60E-04	-1.67	13.1%	6.4%	-10.0%	-26.6%
Thresholds	Coef.	Std. Dev.				
Will rely less than once a month vs. Will rely at least once a month	-0.043	0.577	--	--	--	--
Will rely at least once a month vs. Will rely at least once a week	1.246	0.122	--	--	--	--
Will rely at least once a week vs. Will rely entirely on SAV fleet	3.058	0.728	--	--	--	--
McFadden's R-Square: 0.120			McFadden's adjusted R-Square: 0.090			
Covariates (Model 2: \$2 per mile)						
	Coef.	Z-stat	ΔPr₁	ΔPr₂	ΔPr₃	ΔPr₄
Have heard about Google car (1=yes)	0.821	1.37	-15.3%	11.3%	37.9%	17.8%
ABS form of automation (1=yes)	0.940	2.68	-22.1%	34.1%	24.7%	23.3%
Number of past crash experiences	0.155	1.02	-9.5%	8.9%	28.6%	12.5%
Familiar with carsharing (1=yes)	-2.281	-1.25	22.8%	-22.4%	-42.1%	-69.5%
Distance from workplace (miles)	0.124	2.94	-40.5%	51.7%	21.7%	21.3%
Household size	0.310	1.97	-16.3%	18.5%	27.6%	17.4%
Gender (1=male)	0.690	2.00	-10.5%	13.0%	15.1%	18.2%
U.S. driver license (1=yes)	-1.432	-1.98	12.3%	-11.1%	-26.6%	-24.4%
Number of children	-0.542	-1.97	13.1%	-17.7%	-24.5%	-12.1%
Age	-0.014	-1.20	25.6%	-39.2%	-22.5%	-18.4%
Employment status (1=full-time worker)	0.839	2.28	-15.3%	19.7%	27.9%	16.3%
Area type (1=urban)	0.694	1.36	-11.9%	10.9%	23.4%	12.7%
Population density (per mi ²)	2.64E-04	2.14	-28.4%	35.3%	45.1%	19.6%
Households density (per mi ²)	-6.52E-04	-2.26	17.5%	-25.3%	-22.2%	-18.8%
Basic employment density (per mi ²)	-1.82E-04	-1.12	5.4%	-5.7%	-14.5%	-15.9%
Thresholds	Coef.	Std. Dev.				
Rely less than once a month vs. Rely at least once a month	-1.275	0.625	--	--	--	--
Rely at least once a month vs. Rely at least once a week	0.468	0.448	--	--	--	--
At least once a week vs. Rely entirely on SAV fleet	2.425	0.819	--	--	--	--
McFadden's R-Square: 0.129			McFadden's adjusted R-Square: 0.079			
Covariates (Model 3: \$3 per mile)						
	Coef.	Z-stat	ΔPr₁	ΔPr₂	ΔPr₃	ΔPr₄
Have heard about Google car (1=yes)	1.473	2.21	-10.7%	25.1%	18.0%	36.4%
ABS form of automation (1=yes)	1.431	3.28	-20.3%	51.7%	29.5%	17.2%
Number of past crash experiences	0.183	1.23	-11.3%	29.2%	32.9%	23.6%
Familiar with carsharing (1=yes)	-1.948	-3.05	15.3%	-39.4%	-21.7%	-34.7%
Annual VMT	-5.32E-05	-1.65	20.3%	-52.3%	-17.8%	-10.8%
Distance from downtown (miles)	-0.064	-1.63	10.3%	-22.7%	-22.9%	-26.1%
Gender (1=male)	0.658	1.76	-8.1%	17.8%	14.3%	15.9%
U.S. driver license (1=yes)	-1.864	-2.56	12.1%	-28.2%	-12.1%	-16.2%
Age	-0.029	-2.30	10.2%	-21.8%	-11.5%	-12.5%
Employment status (1=full-time worker)	1.022	2.49	-16.2%	41.5%	10.7%	26.6%
Area type (1=urban)	0.762	1.13	-10.4%	26.4%	17.7%	15.5%
Population density (per mi ²)	9.52E-05	3.06	-13.1%	31.8%	35.1%	17.8%
Retail employment density (per mi ²)	1.70E-04	1.20	-11.4%	27.9%	12.8%	14.4%

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

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

5.3 Willingness to Pay for CVs

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

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

Covariates	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃
Have heard about Google car (1=yes)	1.196	2.15	-32.4%	-17.3%	21.1%
Number of past crash experiences	0.290	2.03	-34.3%	-19.2%	23.2%
Carry smartphone (1=yes)	1.026	1.88	-12.8%	-11.0%	10.2%
Drive alone for work trips (1=yes)	0.895	2.32	-13.1%	-16.3%	12.1%
Drive alone for social trips (1=yes)	0.627	1.44	-21.0%	-11.7%	12.9%
Annual VMT	5.77E-05	1.63	-22.7%	-33.9%	22.1%
Distance from workplace (miles)	0.057	1.71	-20.9%	-17.6%	16.3%
Area type (1=urban)	0.728	1.55	-20.3%	-15.4%	14.1%
Household density (per mi ²)	1.96E-04	1.88	-28.2%	-24.9%	21.5%
Thresholds	Coef.	Std. Dev.			
Not interested vs. Neutral	1.042	0.403	--	--	--
Neutral vs. interested	2.082	0.462	--	--	--
McFadden's R-Square: 0.127			McFadden's adjusted R-Square: 0.083		

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

5.4 Adoption Timing of AVs

Table 7 summarizes the OP model estimates of the adoption timing of AVs (i.e., never adopt AVs, adopt AVs when 50% of friends adopt, when 10 % of friends adopt, or as soon as available in the market). AV adoption by older licensed drivers living farther from their workplace in high basic employment density neighborhoods, ceteris paribus, is more likely to depend on their

1 friends' adoption rates. However, males with higher household income, living in urban
 2 neighborhoods, and who travel more, all other attributes remaining constant, are estimated to
 3 have a practically significant inclination to adopt AVs, with less dependence on their friends'
 4 adoption rates. Number of accidents experienced by the individual and the indicator variables,
 5 whether an individual has heard about Google's self-driving car and if an individual thinks that
 6 ABS is a form of automation, exhibit a positive and practically significant association with AV
 7 adoption timing. This relationship indicates that techy-savvy individuals, who perceive the safety
 8 benefits of AVs, are more likely to adopt them with less dependence on their friends' adoption
 9 rates.

10
 11

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

Covariates	Coef.	Z-stat	ΔPr ₁	ΔPr ₂	ΔPr ₃	ΔPr ₄
Have heard about Google car (1=yes)	1.523	2.76	-34.5%	-10.6%	-9.1%	38.2%
ABS form of automation (1=yes)	0.524	1.66	-24.1%	-34.5%	22.4%	27.9%
Number of past crash experiences	0.323	2.60	-33.8%	-22.1%	-15.8%	51.9%
Log(Annual VMT)	0.408	1.64	-36.3%	-24.1%	14.2%	35.1%
Distance from workplace (miles)	-0.043	-1.44	25.3%	19.4%	-12.3%	-21.6%
Gender (1=male)	0.603	1.98	-37.1%	-15.4%	19.1%	22.1%
U.S. driver license (1=yes)	-1.548	-1.57	20.7%	14.5%	-13.2%	-15.5%
Age	-0.013	-1.30	21.5%	29.8%	-22.3%	-21.7%
Annual household income (\$ per year)	3.89E-06	1.92	-27.8%	-35.9%	31.1%	23.2%
Area type (1=urban)	0.798	2.21	-29.0%	-26.6%	11.1%	32.8%
Basic employment density (per mi ²)	-5.44E-04	-3.41	26.3%	19.0%	-7.3%	-25.4%
Thresholds	Coef.	Std. Dev.				
Never vs. 50% friends adopt	-5.765	0.794	--	--	--	--
50% friends adopt vs. 10% friends adopt	-4.241	0.271	--	--	--	--
10% friends adopt vs. As soon as available	-2.973	0.780	--	--	--	--
McFadden's R-Square: 0.097			McFadden's adjusted R-Square: 0.066			

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

16

17 5.5 Home Location Shifts due to AVs and SAVs

18

19 Table 8 summarizes the OP model estimates of respondents' home-location-shift decisions (i.e.,
 20 shift closer to central Austin, stay at the same location, or move farther from central Austin) after
 21 AVs and SAVs become common modes of transport. Results indicate that respondents with a
 22 greater number of children, living farther from their workplace in high employment density
 23 neighborhoods, and who drive alone for work trips, ceteris paribus, are predicted to shift farther
 24 from central Austin. Perhaps these individuals are excited about lower land prices in suburbs and
 25 are comfortable using their longer commute times pursuing other activities (e.g., working,
 26 talking with friends, and reading). People with Bachelor's degrees, living in high household
 27 density neighborhoods, all other attributes remaining the same, also exhibit a practically
 28 significant inclination to shift farther from central Austin. Perhaps these individuals are
 29 concerned about higher land prices in the highly populated neighborhoods, and are keen to the
 30 benefits of moving to suburban areas after AVs and SAVs become common modes of transport.
 31 In contrast, full-time working males, with higher household income and higher VMT, all other
 32 predictors remaining constant, are likely to shift closer to central Austin, perhaps to appreciate

1 and adopt low-cost SAVs' higher level of service. As expected, tech-savvy respondents (i.e.,
 2 who carry a smartphone and are familiar with carsharing options), living in urban
 3 neighborhoods, ceteris paribus, are estimated to have a practically significant propensity to shift
 4 closer to central Austin.

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

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

7 **Notes:** N_{obs}=347. All Z-stats with |Z-stat|>2.58 are in **bold**, and indicate highly statistically significant predictors.
 8 All ΔPr 's with $|\Delta Pr_i| > 30\%$ are in **bold**, and indicate practically significant predictors.
 9

10 6. CONCLUSIONS

11
 12 Survey results offer many meaningful insights regarding Austinites' perceptions about CAV
 13 technology and related aspects. Average WTP for Level 4 AVs (\$7,253) is much higher than that
 14 of Level 3 AVs (\$3,300). More than 80% of respondents are interested in owning Level 4 AVs.
 15 For roughly 50% of the population, AV adoption rates appear to depend on adoption rates of
 16 friends and neighbors. And more than 80% appear unwilling to pay more for a SAV service than
 17 current carsharing and ridesharing companies are charging. More than 75% of respondents
 18 indicate interest in adding connectivity to their current vehicles, if the cost is under \$100.
 19 Equipment or system failure appears to be the key concern with AV use, while learning how to
 20 use the smart vehicle is the least concerning. Respondents believe fewer crashes to be AVs'
 21 biggest or most likely benefit, and less congestion to be the least likely benefit. The top two
 22 activity picks, while riding in an AV, are looking out the window and talking with friends.
 23

24 This study also estimated how respondent demographics, built-environment factors, and travel
 25 characteristics, impact their opinions about the benefits and concerns for, and adoption of CAVs.
 26 For example, regression-model based WTP estimates, SAV adoption rates (under different

1 pricing scenarios), and AV adoption timing collectively suggest that high-income tech-savvy¹³
2 males, living in urban areas and having greater crash experience have more interest in and a
3 higher WTP for these new technologies, with less dependence on friends' adoption rates¹⁴.
4 Perhaps such individuals are more able to appreciate and evaluate the safety benefits of smart
5 technologies. Surveyed individuals also display a higher inclination to ultimately move closer to
6 central Austin, possibly to enjoy the high-density of low-cost shared fleets (SAVs). In contrast,
7 older licensed drivers expressed less interest in such technologies. They may be concerned about
8 having to learn how to use CAVs and SAVs, and licensed drivers may not be interested in losing
9 the pleasure of driving entirely.

10
11 Individuals that drive more were found to be more likely to adopt AVs, with less dependence
12 upon the adoption rates of friends, and willing to spend more to add Level 4 automation and
13 connectivity, but expressed less interest in adding Level 3 automation or using SAVs costing \$3
14 per mile. This result may be because those who travel longer distances by car can expect to
15 benefit more from safer, more automated, and connected travel with Level 4 technology; and
16 they can perform other activities en route (like work, reading, and talking with friends). This is
17 not so feasible with Level 3 AVs, because drivers must be ready to take over the job of driving,
18 rather quickly. Consistent with past carsharing studies (e.g., Celsor and Millard-Ball 2007),
19 respondents living in denser neighborhoods were more interested in using SAVs under all three
20 pricing scenarios offered here, perhaps due to inconvenient parking facilities and lower vehicle
21 ownership rates in those locations.

22
23 This work's behavioral model parameter and results will be helpful to communities and nations
24 in simulating long-term (e.g., year 2025 and 2040) adoption of CAV technologies, under
25 different energy and vehicle pricing, demographic, and technology scenarios. These forecasted
26 technology adoption rates can help urban planners to start organizing and zoning for
27 development projects in housing, roadways, and complementary infrastructure. For example, if
28 SAVs adoption is expected to take off in a couple of decades, there is a need to plan for parking
29 lots, otherwise infrastructure may be locked-in and might raise future costs in accommodating
30 SAVs. Such results will hopefully usher in smarter, safer, connected, and more sustainable
31 ground transportation systems.

32
33 As suggested by this work, individuals foresee substantial benefits of CAVs, but also perceive
34 hurdles. If such hurdles, or potential barriers, are not understood and managed thoughtfully, they
35 can slow AV adoption rates to socially sub-optimal levels. Armed with such information, public
36 agencies can craft specific policies. For example, they may create opportunities for citizens to
37 "observe" and then "try" CVs, AVs, and CAVs, in experience and better evaluate the "relative
38 advantages" of such technologies. Such experiences are essential ingredients for widespread and
39 rapid technology diffusion (Rogers 2003). Anticipating sizable profit implications, businesses

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

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

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

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

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21 8. REFERENCES

23 Burns, L., Jordan, W., and Scarborough, B. (2013) Transforming Personal Mobility. The Earth
24 Institute, Columbia University, New York. Retrieved from:
25 <http://sustainablemobility.ei.columbia.edu/files/2012/12/Transforming-Personal-Mobility-Jan-27-20132.pdf> (October 6, 2014).

28 Cambridge Systematics (2011). Crashes vs. Congestion: What’s the Cost to Society? Prepared
29 for the American Automobile Association. Retrieved from:
30 http://www.camsys.com/pubs/2011_AAA_CrashvCongUpd.pdf (March 6, 2015).

32 Continental (2015). Continental Mobility Study 2015. Retrieved from: https://www.conti-online.com/www/download/pressportal_com_en/themes/initiatives/channel_mobility_study_en/online_v_mobility_study2015_en/download_channel/mobistud2015_praesentation_en.pdf (March 7, 2015).

37 Celsor, C., and Millard-Ball, A. (2007) Where does carsharing work?: Using geographic
38 information systems to assess market potential. *Transportation Research Record: Journal of the*
39 *Transportation Research Board* 1992: 61-69.

41 Chen, D., Kockelman, K., and Hanna, J. (2015) Operations of a Shared, Autonomous, Electric
42 Vehicle (SAEV) Fleet: Implications of Vehicle & Charging Infrastructure Decisions. Under
43 review for presentation at the 95th Annual Meeting of the Transportation Research Board, and
44 available at http://www.ce.utexas.edu/prof/kockelman/public_html/TRB16SAEVs100mi.pdf.

1 Fagnant, D., and Kockelman, K.M. (2014) Environmental Implications for Autonomous Shared
2 Vehicles Using Agent-Based Model Scenarios. *Transportation Research Part C*, 40: 1-13.
3

4 Fagnant, D. J., Kockelman, K. M., and Bansal, P. (2015) Operations of a shared autonomous
5 vehicle fleet for the Austin, Texas market. Proceedings of the 94th Annual Meeting of the
6 Transportation Research Board (No. 15-1958) and forthcoming in *Transportation Research*
7 *Record*.
8

9 Fagnant, D. J., and Kockelman, K. M. (2015) Dynamic ride-sharing and optimal fleet sizing for a
10 system of shared autonomous vehicles. Proceedings of the 94th Annual Meeting of the
11 Transportation Research Board and submitted for publication in *Transportation*.
12

13 Greene, W. H. (2012). *Econometric Analysis (7th edition)*. Boston: Pearson Education.
14

15 Heide, A., and Henning, K. (2006) The “cognitive car”: A roadmap for research issues in the
16 automotive sector. *Annual Reviews in Control*, 30(2): 197-203.
17

18 J.D. Power (2012) Vehicle owners show willingness to spend on automotive infotainment
19 features. Retrieved from: <http://www.jdpower.com/sites/default/files/2012049-uset.pdf> (March
20 10, 2015).
21

22 Kornhauser, A., Chang A., Clark C., Gao J., Korac D., Lebowitz B., and Swoboda A. (2013)
23 Uncongested Mobility for All: New Jersey’s Area-wide aTaxi System. Princeton University,
24 Princeton, New Jersey. Retrieved from:
25 <http://orfe.princeton.edu/~alaink/SmartDrivingCars/SDC051413.pdf> (July 8, 2015).
26
27

28 KPMG. (2013). Self-driving cars: Are we ready? Retrieved from:
29 [http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/self-driving-](http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/self-driving-cars-are-we-ready.pdf)
30 [cars-are-we-ready.pdf](http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Documents/self-driving-cars-are-we-ready.pdf) (March 11, 2015).
31

32 Kyriakidis, M., Happee, R., and De Winter, J. (2014) Public Opinion on Automated Driving:
33 Results of an International Questionnaire Among 5,000 Respondents. Delft University of
34 Technology (working paper). Retrieved from:
35 http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2506579 (October 15, 2014).
36

37 Litman, T. (2014) Autonomous vehicle implementation predictions. Victoria Transport Policy
38 Institute. Retrieved from: <http://www.vtpi.org/avip.pdf> (March 10, 2015)
39

40 Long, J. S., and Freese, J. (2006) *Regression Models for Categorical Dependent Variables Using*
41 *Stata*. Stata Press. College Station, TX.
42

43 Navigant Research (2014) Self-Driving Vehicles, Advanced Driver Assistance Systems, and
44 Autonomous Driving Features: Global Market Analysis and Forecasts. Retrieved from:
45 <http://www.navigantresearch.com/research/autonomous-vehicles> (October 15, 2014).

1 NHTSA (National Highway Traffic Safety Administration) (2008) National Motor Vehicle
2 Crash Causation Survey. U.S. Department of Transportation, Report DOT HS 811 059.
3 Retrieved from:
4 <http://www-nrd.nhtsa.dot.gov/Pubs/811059.PDF> (October 15, 2014).
5
6 NHTSA (National Highway Traffic Safety Administration) (2013) Preliminary statement of
7 policy concerning automated vehicles. Washington, D.C. Retrieved from:
8 http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf (October 15,
9 2014).
10
11 NHTSA (National Highway Traffic Safety Administration) (2014a) U.S. Department of
12 Transportation announces decision to move forward with vehicle-to-vehicle communication
13 technology for light vehicles. Washington, D.C. Retrieved from:
14 http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf
15 [http://www.nhtsa.gov/About+NHTSA/Press+Releases/2014/USDOT+to+Move+Forward+with+](http://www.nhtsa.gov/About+NHTSA/Press+Releases/2014/USDOT+to+Move+Forward+with+Vehicle-to-Vehicle+Communication+Technology+for+Light+Vehicles)
16 [Vehicle-to-Vehicle+Communication+Technology+for+Light+Vehicles](http://www.nhtsa.gov/About+NHTSA/Press+Releases/2014/USDOT+to+Move+Forward+with+Vehicle-to-Vehicle+Communication+Technology+for+Light+Vehicles) (October 15, 2014).
17
18 NHTSA (National Highway Traffic Safety Administration) (2014b) 2013 Motor Vehicle
19 Crashes: Overview. Retrieved from:
20 <http://www-nrd.nhtsa.dot.gov/Pubs/812101.pdf> (March 26, 2015).
21
22 PUMS (Public Use Microdata Sample) (2013) United State Census Bureau: American
23 Community Survey. Retrieved from:
24 http://www.census.gov/acs/www/data_documentation/pums_data (October 15, 2014).
25
26 Rogers, E. M. (2010) *Diffusion of Innovations (5th edition)*. New York: Free Press.
27 Sajaia, Z. (2008) Maximum likelihood estimation of a bivariate ordered probit model:
28 implementation and Monte Carlo simulations. *The Stata Journal*, 4(2): 1-18.
29
30 Schoettle, B., and Sivak, M. (2014a) A survey of public opinion about autonomous and self-
31 driving vehicles in the US, the UK, and Australia. University of Michigan, Technical Report No.
32 UMTRI-2014-21. Retrieved from:
33 <http://deepblue.lib.umich.edu/bitstream/handle/2027.42/108384/103024.pdf?sequence=1&isAllo>
34 [wed=y](http://deepblue.lib.umich.edu/bitstream/handle/2027.42/108384/103024.pdf?sequence=1&isAllo) (October 15, 2014).
35
36 Schoettle, B, and Sivak, M. (2014b) A survey of public opinion about connected vehicles in the
37 U.S., the U.K., and Australia. University of Michigan, Technical Report No. UMTRI-2014-10.
38 Retrieved from:
39 <http://deepblue.lib.umich.edu/bitstream/handle/2027.42/106590/102996.pdf?sequence=1>
(October 15, 2014).
40
41 Smiechowski J. (2014) Google's driverless prototype is ready to hit the road. Retrieved from:
42 <http://www.hybridcars.com/googles-driverless-prototype-is-ready-to-hit-the-road/> (April 25,
43 2015).
44
45 Underwood, S. E. (2014) Automated vehicles forecast vehicle symposium opinion survey.
Presented at the Automated Vehicles Symposium 2014, San Francisco, CA. Retrieved from:

- 1 <https://drive.google.com/file/d/0B8gGx-CYkV-wREVMTEhHQUxjOwM/edit> . (March 10,
- 2 2015).