

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

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17 **ABSTRACT**

18 Rapid advances in technologies have accelerated the timeline for public use of fully-automated
19 and communications-connected vehicles. Public opinion on self-driving vehicles or AVs is
20 evolving rapidly, and many behavioral questions have not yet been addressed. This study
21 emphasizes AV mode choices, including Americans' willingness to pay (WTP) to ride with a
22 stranger in a shared AV fleet vehicle on various trip types and the long-distance travel impacts of
23 AVs. 2,588 complete responses to a stated-preference survey with 70 questions provide valuable
24 insights on privacy concerns and crash ethics, safety and ride-sharing with strangers, long-distance
25 travel and preferences for smarter vehicles and transport systems. While the starting sample data
26 were relatively demographically unbiased, Texans were purposefully over-sampled, and all
27 statistics adjusted/corrected (via sample weights) to match US demographics on gender, education,
28 income, and age. Weighted results suggest that Americans are willing to pay, on average, \$2073
29 to own AVs over conventional vehicles and an additional \$1078 to maintain/include a manual
30 driving option on such vehicles. Ride-sharing will be popular at 75¢ per mile, under most
31 scenarios, and many Americans are willing to pay \$1, on average, to anonymize their trip ends'
32 addresses. Most are also willing to let children 16 years of age and older have unsupervised access
33 to AVs (both privately owned and shared). Nearly 50% of long-distance travel appears captured
34 by AVs and SAVs in the future, rather than airlines, at least for one-way trip distances up to 500
35 miles.

36 Two hurdle models (which allow for a high share of zero-value responses) were estimated: one to
37 predict WTP to share a ride and another to determine WTP to anonymize location while using
38 AVs. The first two-part model shows how travel time delays, person and household attributes, and
39 land use densities can significantly affect Americans' willingness to share rides. The second hurdle
40 model suggests that traveler age, presence of children, household income, vehicle ownership and
41 driver's license status are major predictors of one's WTP to obscure pick-up and drop-off
42 locations.

43 A binary logit was used to model current mode choice for long-distance (over 50 miles, one-way)
44 travel (between one's private car and an airplane), with household income as the leading predictor.
45 On average, older Americans and/or those with children prefer such travel by car. Finally, a
46 multinomial logit anticipated mode shifts when AVs and SAVs become available and affordable.

1 Everything else constant, private cars remain preferred by older people, but SAVs may be used in
2 the future for more business travel.

3 *Keywords:* Autonomous vehicles, shared, dynamic ride-sharing, travel behaviour survey,
4 willingness to pay, mode choice, privacy.

5 **MOTIVATION**

6 Public opinions regarding vehicle automation and fully automated, or autonomous, vehicles (AVs)
7 is evolving rapidly. Past studies suggest that AVs, once a distant reality, are becoming more
8 acceptable over time, and may be a real mode option in the relatively near future (see, e.g., Vujanic
9 and Unkefer, 2011; Schoettle and Sivak, 2014; Bansal and Kockelman, 2016). Sommer (2013)
10 reported that around half of Americans were concerned about riding in an AV, even though they
11 admitted to the technology's many benefits, and this view was supported by respondents to
12 Schoettle and Sivak's (2014) survey. A more recent U.S. survey, by Kelly Blue Book (2016),
13 suggests that respondents believed conventional vehicles are still safer than AVs – at least for the
14 time-being. Schoettle and Sivak's (2016) second AV survey revealed similar reactions, with more
15 than 35% of U.S. respondents very concerned about AVs, and partial autonomy less feared. Bansal
16 and Kockelman (2016), MIT AgeLab (Abraham *et al.*, 2016), Deloitte (2014) and Lee *et al.* (2017)
17 have all concluded that younger people are more likely to use AVs, so demographic evolution is
18 also important to consider, when anticipating the future use and adoption of advanced transport
19 technologies. Until AVs are widely available in showrooms, at reasonably affordable prices, there
20 will be regular fluctuations in public perceptions in any country or setting. Thus, regular survey
21 efforts, and better surveys, with greater nuance, can make valuable contributions to transportation
22 planning, policymaking, and vehicle production decisions.

23 With ride-hailing applications maintaining a steady increase in mode shares, especially in dense
24 settings like San Francisco (SFMTA, 2015), and several studies illuminating the operational
25 benefits of dynamic ride-sharing (DRS) (see, e.g., Agatz *et al.*, 2010; Bischoff *et al.*, 2016; Fagnant
26 and Kockelman, 2016; Loeb *et al.*, 2017; Farhan and Chen, 2017), a shift towards shared AVs
27 (SAVs) with DRS options is expected. However, detailed studies on DRS have not yet been
28 conducted. Bansal and Kockelman (2016) estimated SAV use for different pricing levels, but do
29 not delve into ride-sharing. Quarles and Kockelman (2018) have recent, unpublished results that
30 suggest about 16% of Americans are willing to share rides with strangers by paying about 40
31 percent less (e.g., 60 ct/mile rather than \$1 per mile of SAV use). However, response-time or
32 waiting time analysis has not been carried out. To the best of the author's knowledge, only one
33 study on the other side of the world, by Krueger *et al.* (2016) captures such nuances, by modeling
34 a discrete choice decision between SAVs without DRS, SAVs with DRS and a respondent-specific
35 travel alternative. They concluded that DRS is a preferred option among the young people and the
36 people who regularly use carsharing services but also mentioned their limitations because of the
37 hypothetical bias. Similar studies in the United States have not yet been conducted.

38 Privacy and data security are another relevant topic, with one survey suggesting that privacy is
39 Americans' top concern when choosing to not use AVs (Schoettle and Sivak, 2014). Existing work
40 in this area lacks many details: e.g., what are people willing to pay for privacy-enforcing measures?
41 Related to this, automation can pose ethical dilemmas. Bonnefon *et al.* (2016) and Goodall (2017)
42 believe that public opinion must be considered in crash-response programming and the like.
43 Jenkins (2016) and Lin (2017) have described several possible outcomes of an inevitable crash
44 scenario and Fleetwood (2017) censured algorithms that teach AVs to choose targets by force,
45 arguing that they should not be readily allowed for public use. However, the public perception of
46 what is most ethical in crash response contexts, and other situations, like who is to blame for a
47 computer's decision or criteria to pass to be allowed to use SAVs, is yet to be determined. This
48 survey adds new questions and public opinions to that discussion.

1 Finally, the long-distance (LD) travel implications of AVs are an important consideration.
2 LaMondia *et al.* (2016) introduced AVs as new mode for LD trips originating in Michigan. Bansal
3 and Kockelman (2016, 2017) suggested that LD-trip frequency may well double, and Perrine *et*
4 *al.* (2017) are predicting major losses in U.S. airline revenues, long term, once AVs are widely
5 available. However, many details are missing, especially questions that probe actual Americans
6 on these topics.

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

10 **SURVEY DESIGN & DATA PROCESSING**

11 The survey consists of 70 questions, tackling various aspects of AV and SAV use, including ride-
12 sharing preferences, privacy and security concerns, ethical implications of crash response
13 algorithms, long-distance travel shifts, and future travel choices, with each subject section having
14 about 5 to 8 questions.

15 The section on current AV perceptions included questions on impressions of and WTP for AVs,
16 SAV use, and DRS with strangers. Questions regarding an acceptable age for children/young
17 people to travel individually or in a group were also asked, along with questions regarding
18 opportunities for serving persons with disabilities. AA slider response was used to obtain
19 continuous responses on WTP, including for DRS with a stranger - by time of day (night vs.
20 daytime) and assuming different time delays. The value of providing one's location en route (to a
21 close friend or family member, to increase travelers' sense of security) was also addressed, when
22 sharing an SAV ride with an unknown person.

23 To assess the ethical implications, three distinct ethical dilemmas were posed to the respondents:
24 two regarding AV crashes with a pedestrian and other cars on the road, and one addressing crash
25 responsibility. Questions on LD travel were based on mode-choice preferences for different types
26 of trips and a respondent's typical LD trip. A demographic section was included towards the
27 survey's end, to provide control variables and correct for various sampling biases, to better
28 represent the U.S. population.

29 **Data Collection**

30 Survey Sampling International's (SSI) panel of Americans was used to access respondents from
31 across the United States. Nearly 10,000 Americans were targeted before the required sample
32 attributes were obtained, due to two screening procedures. The first screen blocked respondents
33 from accessing the survey in its entirety if they failed to answer two initial basic questions
34 regarding AVs and SAVs, after relevant information was provided. The second level of screening
35 was done by removing respondents who took less than 15 minutes to complete the survey, since a
36 low response time was deemed unrealistic for anyone going through this 70-question long survey.
37 Both screens helped ensure respondents were intellectually engaged, and paying attention.

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

45

46

1 Population Weighting

2 The 2,588 complete responses were associated with household and person-level weights to ensure
 3 that all reported statistics and regression analyses reflect the broader population of interest. The
 4 U.S. Census Bureau's Public Use Microdata Sample (PUMS) for years 2011-2015 provided
 5 national and state percentages across various classifications: location (Texas vs. U.S.), income and
 6 race, household size and worker count, vehicle ownership, age, gender, educational attainment and
 7 marital status. Certain demographics were under-represented (e.g., males who had not finished
 8 high school) and some others were overrepresented (e.g., gender ratio was 47/53 rather than 49/51,
 9 24% of the sample were people 65 years or older rather than 18%), resulting in slightly higher
 10 weights. MATLAB code performed iterative proportional fitting over all the combinations of
 11 dimensions, ending once categorical percentages fell within 0.001% of the population percentages.
 12 Population-weighted sample characteristics are shown in Table 1. All of the following results
 13 reflect these adjustments to raw sample statistics.

Table 1: Survey Data's Population-Weighted Summary Statistics

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

14

15 SUMMARY STATISTICS

16 Current AV Perceptions

17 As noted above, the survey's first section gauged perceptions of AVs. Table 2 summarizes the
 18 public's opinion on driving preferences, benefits offered with AV use, concerns in using them, and
 19 considerations at play in owning an AV. In general, Texans' responses do not differ by much, in
 20 any survey section, but there are some questions in which notable differences emerge. For
 21 example, 36.4% Americans enjoy driving conventional vehicles and do not plan on using AVs in
 22 the future, while just 26.7% of Texans give that response. 31.8% Texans (vs. 29.4% of Americans
 23 overall) want to keep the AV option open for their travel, even though they enjoy driving, while
 24 15.0% of Texans (vs. 11.6% of Americans) expect to prefer AV use to driving.

25 The great majority (92.9% Americans and 90.5% of Texans) believe that safety is a major AV
 26 benefit, yet over 60% are concerned that AVs may not be safe enough, with faulty software being
 27 a top concern. The mixing of AVs and conventional vehicles on public roadway is also an
 28 important concern. Top factors favoring AV ownership, instead of U.S. households relying more
 29 on SAVs, are the ability to store items in one's own vehicle and keeping one's own vehicle
 30 relatively clean or free of other's germs, while enjoying greater privacy and flexibility in their AV
 31 use decisions. It was unusual to find an AV's self-parking ability to be chosen by less than 2% of

1 Americans as a major benefit. Proxy information about individuals with a disability was assessed,
 2 and 59.2% of Americans and 60.3% of Texans acknowledged that they knew at least one person
 3 among their immediate family, relatives, friends or neighbors, who was disabled and would benefit
 4 from the use of SAVs.

5 **TABLE 2: Driving Preferences and Factors Affecting AV Ownership**

Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
<i>Current driving preferences</i>					
Enjoys driving and does not plan to use AVs	36.4%	26.7%	Does not like driving and will prefer AV use	11.6%	15.0%
Enjoys driving but will prefer some AV use	29.4%	31.8%	Prefers only non-motorized modes of travel	2.9%	0.9%
Prefers some driving as well as some AV use	17.5%	14.0%	Does not like driving but does not plan to use AVs	0.5%	1.3%
<i>Expected major benefits of AVs & SAVs</i>					
Safety improvement offered by AVs	92.9%	90.5%	Reliability	1.7%	5.1%
Congestion relief	2.8%	1.9%	Self-parking	1.4%	2.2%
Convenience of travel	2.6%	2.0%			
<i>Expected major concerns of AVs</i>					
Safety against crashes offered by AVs is still questionable				66.5%	62.5%
Faulty software in AVs				75.6%	71.1%
Confusion among human drivers and AVs on the streets				49.9%	51.9%
Privacy breaches inside AVs				16.9%	19.1%
Others tracking one's home or work location is easier with AVs				30.3%	39.3%
<i>Factors causing one to own AVs instead of sharing SAVs</i>					
Parking space availability	6.1%	7.4%	Privacy benefits of owning an AV	19.9%	15.4%
Relative cost of AVs over conventional cars	15.2%	11.0%	Hygiene concerns about SAVs that are not clean due to previous use and possible presence of germs	8.2%	11.6%
Availability of children's car seats in one's own AV	13.3%	14.7%	Security and safety	0.4%	1.3%
Ability to leave small items behind in one's own AV	21.4%	22.7%			
Storage space for large items	15.6%	15.4%			

6
 7 Americans appear WTP, on average, \$2073 more to own an AV as compared to a conventional
 8 vehicle, plus another \$1078 if that new AV includes a human-driving mode option.

9
 10
 11

1 Ride-Hailing and SAV Use

2 The survey's second section emphasizes ride-hailing applications and SAV use, including
3 respondents' willingness to allow children to use AVs. Responses, suggest that only 32.5% of
4 Americans (and 33.3% of Texans) have personal ride-hailing experience. Among these ride-
5 hailing users, only 27.3% (across the U.S., and 14.7% from Texas) have shared their rides with
6 strangers.

7 Texans appear to believe that children should be at least 17 years to use privately owned
8 (household) AVs, shown in Table 3, while the average American appears comfortable with a 16-
9 year-old threshold. However, 62.2% of Americans were against the idea of sending their own
10 children, at any age, in an SAV, without an adult escort. Texans were slightly more comfortable
11 in such private-AV-use behavior, with an acceptance rate of 45.7%.

12 **TABLE 3: Americans' Perspective on Ride-Hailing and SAV Use**

Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
<i>Age appropriate for RIDE-HAILING services</i>			<i>Age appropriate for children to use parents' AVs</i>		
Median age (in years)	16.0	16.0	Median age (in years)	16.0	16.0
Average age (in years)	16.0	16.3	Average age (in years)	16.4	17.4
Response Variable			U.S.	Avg. Age	Texas
<i>Is it acceptable to allow a group of children use an SAV without adult supervision?</i>					
Yes, if there are all at least XX years old.			26.2%	16.2 yrs	27.9%
Yes, if any one child in the group is at least XX years old.			23.0%	16.8 yrs	30.9%
No, it is not acceptable to send children in SAVs.			62.2%		54.3%

13

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

15 Public opinion on ride-sharing with strangers (while using an SAV) was assessed in detail. First,
16 a hypothetical 5-mile SAV trip was presented and rising travel times (to reflect delay from adding
17 another passenger) were added to this trip. Next, each respondent's willingness to share the same,
18 hypothetical, 5-mile trip during the night was assessed. Maximum travel delays for sharing trips
19 during the middle of the day and during the night were identified. Any added willingness to use
20 DRS when their location was continuously available/broadcast to a family member (or friend) was
21 also recorded, for both cases of day and nighttime trip-making. In addition to these preferences,
22 the ideal cost of using an SAV in order to willingly let go of a currently owned household vehicle
23 was obtained for different SAV response times (i.e., the time taken between a trip request and the
24 SAV's arrival at the traveler's origin). All these results are summarized in Table 3.

25 As shown in Table 4, only 62.5% Americans and just 54.9% of Texans may be willing to share
26 their ride with strangers when no delay accrues (i.e., no time is added to their 5-mile trip). This
27 willing-to-share-rides pool of respondents reported an average WTP of 74¢ per trip-mile.
28 Interestingly, all scenarios of added travel time returned a similar average. Americans (and Texans)
29 may be more interested in their trip distance than their travel time, once they have opted to share
30 their ride.

1 **TABLE 4: Ride-Sharing Preferences During Middle of the Day**

Response Variable			U.S.	Texas			
<i>Willingness to use SAV with strangers, no additional time</i>							
Yes			22.5%	30.0%			
Maybe			40.0%	24.9%			
No			37.5%	35.1%			
Average WTP (per mile)			\$0.74	\$0.71			
Response Variable	U.S.	Texas	Response Variable	U.S.	Texas		
<i>Willingness to use SAV with strangers, 5 min. additional time</i>			<i>Willingness to use SAV with strangers, 15min. additional time</i>				
Yes			18.5%	23.2%	Yes	6.0%	8.8%
Maybe			34.8%	31.9%	Maybe	19.1%	21.6%
No			46.7%	45.0%	No	75.0%	69.6%
Average WTP (per mile)			\$0.73	\$0.69	Average WTP (per mile)	\$0.79	\$0.65
<i>Willingness to use SAV with strangers, 30 min. additional time</i>			<i>Willingness to use SAV with strangers, 1 hr. additional time</i>				
Yes			2.8%	2.7%	Yes	2.2%	2.2%
Maybe			7.9%	15.6%	Maybe	4.2%	5.7%
No			89.4%	81.7%	No	93.6%	92.1%
Average WTP (per mile)			\$0.77	\$0.65	Average WTP (per mile)	\$0.74	\$0.62

2
 3 Table 5 describes willingness to share rides (including trip durations, in DRS mode) during the
 4 day and the night. Very few Americans (just 4.4%, vs. 11.0% of Texans) seem willing to share
 5 their rides at night (though this may well change, as people become more accustomed to SAV and
 6 DRS services in the future). Of those willing to use DRS during the middle of the day, 4.0% more
 7 Americans are willing if the service is offered only to people without a prior criminal record.
 8 Americans (and Texans) are willing to pay a 10¢-per-mile premium, on average, to share a ride
 9 during the night (presumably because they need more chauffeured trips at night [for consumption
 10 of alcohol, for example] or expect lower supply of SAVs at night). On average, respondents are
 11 more willing to tolerate trip delays at night, presumably because time constrains (on work and
 12 school arrivals, for example) are more severe during the daytime.

13 **TABLE 5: Ride-Sharing Preferences at Night**

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

<i>Maximum trip duration for a shared ride in an SAV during the night (in minutes)</i>					
Mean	34.8	35.4	Median	29.0	30.0
<i>Maximum trip duration between day and night among those willing to share a ride both in the day and in the night</i>					
Average during the day (in minutes)	40.4	47.5	Average during the night (in minutes)	34.8	35.4

1
2 Additional DRS features, like location information broadcast to family or friends for safety
3 purposes, resulted in more people (roughly 15%) willing to share rides (during the day and at
4 night). However, as seen in Table 6, more than 60% of Americans (and Texans) remained
5 unwilling to ride-share in an SAV. And over 90% seemed hesitant about paying for such a service.
6 Among those willing to pay for such a service, Texans appear to be more concerned about their
7 safety than other Americans.

8 **TABLE 6:** Effects of Ride-sharing Trip Location being Broadcasted

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

9
10 Table 7 summarizes the cost that an SAV must be operated at, for different response times, so that
11 the respondent is comfortable letting go of an existing household vehicle. The American
12 Automobile Association (AAA, 2016) estimates that current vehicle ownership and operating costs
13 average 50 to 80 cents per mile, once depreciation of purchase costs is reflected. Those costs can
14 be higher or lower for vehicles driven fewer or more miles per year than the typical U.S. household
15 vehicle. Interestingly, respondents are willing, on average, to pay about that same amount for SAV
16 access – and Texans tend to offer more money than the average American. SAV users can avoid
17 vehicle maintenance and parking costs and hassles, but they cannot guarantee how quickly SAVs
18 will get to them, like they can when walking to their parked vehicle. Actual SAV system
19 experiences will end up impacting everyone's WTP, and service times may vary a fair bit by

1 location (e.g., urban vs. suburban trip ends). It is an interesting evolution of supply and demand
 2 that should one day play out around the world.

3 **TABLE 7:** Cost of SAVs at Different Response Times to Persuade Reduction in Current Vehicle
 4 Ownership

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

5

6 Privacy Concerns using AVs and SAVs

7 Privacy is not on top of respondents' minds when AV-related concerns are requested at the survey
 8 start (Table 2). However, when targeted as a separate topic, more privacy-related concern was
 9 observed. Table 8 demonstrates this, with 89% of Americans (and 83% of Texans) to at least some
 10 privacy concerns. However, many respondents (39.8% of Americans and 40.6% of Texans) appear
 11 unwilling to pay to anonymize their location while using SAVs. Respondents were also asked to
 12 rate their levels of comfort when their location data is used for different socially meaningful
 13 purposes. Nearly 48% Americans, on average, were comfortable or somewhat comfortable with
 14 this data being used for policing activities, managing traffic and for general community
 15 surveillance. However, more than half were against targeted advertising use.

16

TABLE 8: Privacy Concerns Related to AVs and SAVs and WTP for Privacy

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

Very comfortable	14.5%	14.1%	Very comfortable	3.8%	3.4%
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2 **Crash Ethics While Using AVs**

3 Two distinct crash scenarios were presented in the survey, describing an AV crashing into a group
4 of pedestrians in one case and crashing into other cars on the road in another. Respondents picked
5 from a broad list of options to describe ethical and non-ethical crash outcomes. Table 8 opinions
6 regarding the most ethical outcomes along with the person or business that should be held
7 accountable for such events.

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

17

TABLE 9: Crash Choices and Responsibilities

Response Variable	U.S.	Texas
<i>Scenario 1: AV inevitably crashing into a group of pedestrians</i>		
AVs must not change course, no matter what, and must crash into whoever is ahead.	54.2%	47.6%
The crash must should occur without any biases or preferences on age, race and gender of individuals in the group of pedestrians.	24.8%	26.4%
Children must be avoided under all circumstances.	19.2%	21.1%
Respondent is unsure if any of the options correctly describes an ethical outcome.	6.8%	9.2%
AVs must avoid crashing into friends identified in this group.	3.3%	4.2%
The AV must change into its human-driven operation mode so that the human can instinctively decide.	0.7%	0.3%
The occupant of the AV must be sacrificed for agreeing to use such a vehicle.	0.3%	0.2%
<i>Scenario 2: AVs inevitably crashing into other vehicles on the road</i>		
The crash must occur without any biases on vehicle-type, value or insurance.	38.4%	38.9%
AVs must not change course, no matter what, and must crash into the first vehicle it encounters.	31.8%	31.8%
The crash must occur such that the overall harm to human-life is minimized (e.g., AVs can crash into bigger vehicles.)	19.9%	19.5%
The crash must occur such that the harm to the AVs occupants is minimized.	11.4%	12.7%

Respondent is unsure if any of the options correctly describe an ethical outcome.			5.9%	6.5%	
The crash must occur such that cars identified as belonging to a friend must not be damaged.			1.6%	2.7%	
Response Variable	U.S.	Texas	Response Variable	U.S.	Texas
<i>Who should take responsibility for all damages in an unavoidable crash?</i>					
The AV manufacturer should take responsibility.	60.9%	59.7%	Respondent does not hold an opinion.	5.0%	4.8%
The programmer who built the AV's algorithm.	23.2%	23.2%	Should be decided by insurers.	1.4%	0.4%
Crashes will continue to occur; no one needs to take responsibility.	19.6%	22.2%	The courts should decide.	0.6%	1.7%
The individual who owns the AV and knows the risks that entail operating the vehicle should be held responsible for the crash.			0.4%	1.0%	

1

2 **Long-Distance (LD) Travel Choices**

3 Various LD trip-making behaviors were investigated, including frequency of LD trip-making (per
4 month), the longest trip made over the past year, share of LD trips with other persons (e.g., alone
5 versus with friends, family, or colleagues), and mode preferences (across trip purposes and
6 distance bands). Most LD trips occur with family members, and most respondents travel more LD
7 often for personal trips than for business or vacation.

8 Over 80% of Americans (and Texans) prefer to use their own household vehicle for any non-
9 business trip type under 500 miles. With the introduction of AVs and SAVs, conventional-
10 (human-driven) vehicle choice for non-business LD trips under 500 miles drops to 40%. AVs and
11 SAVs enjoy a combined mode preference of 49.6% for business trips between 50 and 500 miles
12 (one-way distance). For distances over 500 miles (one-way), air travel is preferred, for all trip
13 types. Respondents may be expecting that they somehow can better afford air travel in the future,
14 since this mode split is not consistent with current airline use splits. These results will be game-
15 changers when included in LD mode choice analyses in all statewide or national-level models.

16 **MODEL ESTIMATION**17 **Willingness to Pay for Dynamic Ride-Sharing**

18 WTP for DRS in an SAV was estimated in two parts, to reflect the high number of respondents
19 unwilling to share rides with strangers, as shown in Table 10.

20 **Table 10:** Respondents Unwilling to Share Rides (in an SAV, for Different Added Times)

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

30	89.37
60	93.63

1 The two-part model is motivated by Cragg's (1971) hurdle regression specification and was
 2 estimated using Stata software (StataCorp., 2015). This approach assesses the hurdle beyond which
 3 a particular event occurs. Here, the hurdle is one being WTP to share a ride and is estimated as a
 4 selection variable, s_i , using the maximum likelihood techniques while allowing for unobserved
 5 heteroscedasticity (across respondents) as a function of age. Correlation between responses from
 6 the same respondent was accounted for using data stratification in Stata, and an independent and
 7 identically distributed epsilon is assumed between respondents. A zero-dollar lower bound for
 8 each respondent's WTP was imposed as shown below., where \mathbf{x}_i is the vector input of predictor
 9 variables affecting this \$0 selection, $\boldsymbol{\beta}_1$ is the associated vector of model coefficients and $\varepsilon_{i,1}$ is
 10 (assumed to be) a normally-distributed error term.

$$11 \quad s_i = \begin{cases} 1 & \text{if } \mathbf{x}_i \boldsymbol{\beta}_1 + \varepsilon_{i,1} > 0 \\ 0 & \text{otherwise} \end{cases}$$

12 The second part of the model estimates the specific amount that one is WTP using an exponential
 13 regression function, in cases where $s_i = 1$. Both equations are estimated simultaneously using
 14 maximum likelihood estimation (MLE). An exponential regression function ensures that WTP
 15 estimates can only be positive, with \mathbf{z}_i serving as the vector of predictors or explanatory variables,
 16 $\boldsymbol{\beta}_2$ the vector of parameters to be estimated, and $\varepsilon_{i,2}$ as another set of independent, identically
 17 distributed normal error terms.

$$18 \quad Y_i = \exp(\mathbf{z}_i \boldsymbol{\beta}_2 + \varepsilon_{i,2})$$

19 Table 11 shows the estimated parameters for both the selection model and exponential regression
 20 model. As expected, the travel time added via ride-sharing significantly affects respondents'
 21 decision to ride-share. Presence of a worker in the household reduces one's willingness, perhaps
 22 because workers have more constrained activity patterns, and so desire or need more independent
 23 travel. Interestingly, older people (everything else constant) and those with drivers' licenses are
 24 estimated to be less likely to share a ride. Those in households with annual incomes between
 25 \$75,000 and \$125,000 appear more likely to share a ride, as compared to other income brackets.
 26 It is possible that lower income brackets cannot simply afford to use an SAV, while those in higher
 27 income brackets prefer private rides.

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

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

1 be WTP a lower value, assuming they are already willing to share a ride, in this hurdle model
 2 specification.

3 **Table 11:** Model Estimation Results for WTP to Share a Ride

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

4

5 The change in response when each of the covariates was changed by one standard deviation
 6 was computed to understand how the expected WTP to share rides may change and this is tabulated
 7 in Table 12. For continuous variables, like respondent's age, the marginal expected value of WTP
 8 is calculated one standard deviation away from the mean age, in both directions. For indicator
 9 variables, the change in responses are determined by completely switching from a base level (like
 10 0), to the next or subsequent levels (for example, 1, 2, or 3) and then calculating the marginal
 11 expected value of WTP at that point. Essentially, a continuous covariate's mean, plus/minus one
 12 standard deviation, is used to compute the new mean WTP for the sample and this percent change
 13 with respect to the previous mean is tabulated and for indicator variables, these percent change
 14 values are calculated by assuming all responses are at a high (that is, 1) or some intermediate point
 15 (like 2, 3 or 4 in a multi-level indicator) and then calculating the new mean. Computed changes in
 16 expected value of WTP with respect to the initial mean suggests that the lack of a driver's license

1 affects mean values the most, by increasing it by 38%. When everything else is constant, a one
 2 standard deviation in average age of Americans can reduce the expected WTP by 27%. However,
 3 as Americans continue to age, the increase in average age will bring it down. As more people fall
 4 into the middle-class household income category, results suggest that there will be a 26% increase
 5 in average WTP to share rides.

6 **Table 12:** Covariate Elasticities for WTP to Share Rides

Independent Variables		% Change in WTP
Worker present in the household?	Y	+19.6%
	N	-7.84%
Age of respondent (in years)	+1SD	-26.86%
	-1SD	+18.07%
Have U.S. driver's license?	Y	-4.73%
	N	+38.19%
Household income between \$75k and \$125k?	Y	+26.06%
	N	-6.61%
Has attended some college?	Y	+6.71%
	N	-10.02%
Population density (per square mile)	+1SD	-19.54%
	-1SD	+10.49%
Employment density (per square mile)	+1SD	+21.56%
	-1SD	-5.92%

7

8 **Willingness to Pay to Anonymize Location While Using SAVs**

9 A similar hurdle exponential regression was estimated to determine one's WTP to
 10 anonymize pick-up and drop-off locations while using SAVs. Table 13 shows the estimated
 11 coefficients for the two-part model. As expected, respondents who are concerned about privacy
 12 are more likely to be WTP to anonymize their location. Disabled people and females are more
 13 likely to be WTP, perhaps because they feel that they are relatively vulnerable and make an easier
 14 target for criminal behaviors. Vehicle ownership is also estimated to increase a respondent's WTP
 15 to a non-zero value for this anonymization benefit. Older people and those in smaller households
 16 are estimated to be less likely to pay to anonymize their locations. Household income is an
 17 interesting factor in this decision, since it oscillates back and forth between different income
 18 groups. In terms of one's level of payment, model results suggest that older persons and Caucasians
 19 are more WTP than those with a driver's license or those in households with more children.

Table 13: Model Estimation Results for WTP to Anonymize Location While Using SAVs

Selection Model		
<i>Independent Variables</i>	<i>Coefficients</i>	<i>T-stat</i>
Constant	-0.40	-1.61
Concerned about privacy?	1.73	9.26

Table 13: Model Estimation Results for WTP to Anonymize Location While Using SAVs

No disability?	-0.69	-5.75
Household owns 1 vehicle?	0.60	5.40
2 vehicles?	0.67	5.48
3 vehicles?	0.63	4.64
4+ vehicles?	0.66	4.14
Household size equal to 2?	0.16	2.02
equal to 3?	0.27	2.67
equal to 4+?	-0.11	-1.13
Household workers equal to 1?	-0.12	-1.54
equal to 2?	-0.10	-1.07
equal to 3?	-0.47	-3.14
equal to 4+?	-0.51	-1.89
Age of respondent (in years)	-0.02	-11.14
Is Male?	-0.35	-6.35
Household income: < \$20,000	0.72	5.51
Or < \$30,000	0.13	1.06
Or < \$40,000	-0.02	-0.14
Or < \$50,000	0.18	1.31
Or < \$60,000	0.17	1.19
Or < \$75,000	0.33	2.41
Or < \$100,000	0.25	1.87
Or < \$125,000	0.17	1.19
Or < \$150,000	0.68	3.96
Or < \$200,000	0.14	0.84
Or > \$200,000	0.70	4.06
Exponential Regression Model		
<i>Independent Variables</i>	<i>Coefficients</i>	<i>T-stat</i>
Constant	-0.86	-7.23
Age of respondent (in years)	-0.4E-2	-3.24
Have U.S. driver's license?	0.26	3.72
Caucasian?	-0.14	-3.10
Household has 2 or less children?	0.48	6.11
Household income: < \$20,000	0.23	2.45
Or < \$30,000	0.52	5.20
Or < \$40,000	0.39	3.67
Or < \$50,000	0.18	1.77
Or < \$60,000	0.08	0.72
Or < \$75,000	0.41	4.07

Table 13: Model Estimation Results for WTP to Anonymize Location While Using SAVs

Or	< \$100,000	0.38	3.94
Or	< \$125,000	0.38	3.60
Or	< \$150,000	0.36	3.22
Or	< \$200,000	0.54	4.52
Or	> \$200,000	0.06	0.56
Population density (per square mile)		-0.2E-4	-3.13
Employment density (per square mile)		0.1E-4	2.48
<i>Variables with Heteroscedasticity</i>			
Age of respondent (in years): Exponential model		-0.6E-2	-16.62
<i>Fit statistics</i>			
Final log-likelihood		-705.4893	
Pseudo R-square		0.6140	
Likelihood Ratio Chi-Square		2244.21	
Number of observations		2,588	

1

2 The changes in responses and marginal expected value of WTP is calculated for this model
3 similarly to the previous hurdle model and is shown in Table 14. The percentage deviation of the
4 expected value of WTP helps identify potential policy impacts to privacy and location
5 anonymization decisions. Negative changes on all covariates showed that, although Americans
6 seem to want privacy and may be willing to pay for anonymized trips, it may be unlikely that
7 privacy will of trip locations will be a concern in the future. They also suggest that, moving
8 forward, with the aging population and increasing average wages, there may be a decline in dollar
9 amount that Americans are WTP to anonymize a trip.

10

Table 14: Covariate elasticities for WTP to Anonymize Location in an SAV

Independent Variables	% Change in WTP
No disability?	Y: -35.14%
	N: -13.14%
Household owns 0 vehicles?	-55.58%
1 vehicle?	-33.06%
2 vehicles?	-30.49%
3 vehicles?	-32.00%
4+ vehicles?	-30.85%
Household size equal to 1?	-36.15%
equal to 2?	-30.34%
equal to 3?	-26.54%
equal to 4+?	-40.16%
Household workers equal to 0?	-29.73%

equal to 1?	-33.98%
equal to 2?	-33.25%
equal to 3?	-46.97%
equal to 4+?	-48.47%
Age of respondent (in years)	+1SD: -55.57%
	-1SD: -15.00%
Is Male?	Y: -40.04%
	N: -27.38%
Household income: < \$20,000	-20.95%
Or < \$30,000	-32.46%
Or < \$40,000	-42.49%
Or < \$50,000	-40.00%
Or < \$60,000	-42.33%
Or < \$75,000	-28.55%
Or < \$100,000	-32.34%
Or < \$125,000	-35.31%
Or < \$150,000	-18.09%
Or < \$200,000	-31.93%
Or > \$200,000	-26.23%
Have U.S. driver's license?	Y: -32.77%
	N: -39.13%
Caucasian?	Y: -35.15%
	N: -31.29%
Population density (per square mile)	+1SD: -36.51%
	-1SD: -29.98%
Employment density (per square mile)	+1SD: -29.50%
	-1SD: -34.41%

1

2 Long-Distance Mode Choice with & without AVs and SAVs

3 Mode choice for long-distance travel was studied by first estimating a binary logit model
4 when there are no AVs and SAVs available. Then, a multinomial logit model was estimated based
5 on another survey question that included these modes. Correlation is allowed between responses
6 from the same respondent and an independent identically distributed Gaussian error term was
7 assumed for observations between different respondents.

8 Table 15 shows the estimated coefficients as well as changes in the expected mode share
9 of airplane for the binary logit model between the mode choices of a private car and an airplane.
10 The private car was chosen as the base case and all coefficients can be interpreted with respect to
11 this. The model suggests that business and recreational trip types are typically completed by
12 airplanes. Trips greater than 500 miles, as expected, also use airplane for travel. Households
13 owning one or more vehicles are less likely to prefer flying, provided everything else is constant.
14 Single-person households seem the most interested in preferring to fly. Changes in household
15 occupancies estimates a 32% increase if more single households were to exist. It is interesting to

1 see the gradual change in preference among different income groups towards air travel. This is
 2 shown considerably well by their elasticities (the gradual change from negatives to positives for
 3 air travel). It is expected that wealthier households are more likely to fly to their destination,
 4 irrespective of business or pleasure. Interestingly, older people prefer to travel in their own vehicle
 5 as compared to the time-luxury of air travel. This could be because of lowered comfort level in an
 6 airplane as compared to that of their own vehicle. Caucasians prefer to drive their own car as
 7 compared to flying and this is most likely due to the heritage of driving in America. Households
 8 with children are unlikely to travel by air as compared to households without children.

Table 15: Model Estimation and Covariate Elasticities for Mode Choice in Long-Distance Travel without AVs and SAVs

Binary Logit Model				
<i>Independent Variables</i>	<i>Coefficient</i>	<i>T-stat</i>	<i>Changes in Mode Share</i>	
Alternative: Airplane (Base – Private Car)	Constant	0.76	1.15	
	Trip Type – Personal?	(base)		-20.63%
	– Business?	0.97	5.48	+23.56%
	– Recreation?	0.71	4.85	+10.87%
	Distance: 100 – 500 miles	(base)		-41.70%
	> 500 miles	1.78	13.69	+43.95%
	Household owns 0 vehicles	(base)		+38.09%
	1 vehicle?	-0.69	-1.38	+5.20%
	2 vehicles?	-0.87	-1.69	-2.88%
	3 vehicles?	-0.79	-1.42	+0.91%
	4+ vehicles?	-1.45	-2.25	-26.72%
	Household size equal to 1?	(base)		+32.25%
	equal to 2?	-1.30	-4.84	-25.89%
	equal to 3?	-0.50	-1.42	+8.23%
	equal to 4+?	-0.67	-1.37	+0.82%
	Household workers equal to 0?	(base)		+14.44%
	equal to 1?	-0.62	-2.58	-13.40%
	equal to 2?	-0.16	-0.52	+7.02%
	equal to 3?	-0.59	-1.18	-12.31%
	equal to 4+?	0.52	0.69	+39.84%
	Age of respondent (in years)	-0.01	-2.12	+1SD: -12.39% -1SD: + 8.70%
	Caucasian?	-0.68	-3.37	Y: -11.32% N: +19.60%
	No child in the household	(base)		+12.77%
	Children in the household: 1 child?	-1.57	-4.51	-49.92%
	2 children?	-0.22	-0.43	+2.53%
	3 children?	-0.25	-0.40	+0.99%

Table 15: Model Estimation and Covariate Elasticities for Mode Choice in Long-Distance Travel without AVs and SAVs

	4+ children?	-1.59	-2.12	-50.57%
	Household income: < \$20,000	-1.53	-2.46	-64.76%
	Or < \$30,000	-1.09	-2.23	-52.29%
	Or < \$40,000	-0.58	-1.15	-34.44%
	Or < \$50,000	-0.36	-0.77	-25.43%
	Or < \$60,000	-0.78	-1.59	-41.89%
	Or < \$75,000	0.33	0.64	+5.76%
	Or < \$100,000	0.51	1.13	+14.70%
	Or < \$125,000	0.94	1.90	+37.07%
	Or < \$150,000	1.27	2.39	+54.04%
	Or < \$200,000	1.17	2.35	+48.82%
	Or > \$200,000	2.20	3.56	+100.16%
	Population density (per square mile)	0.4E-4	1.39	+1SD: +14.08%
				-1SD: - 6.60%
	Employment density (per square mile)	-0.7E-4	-1.31	1SD: -13.36%
				-1SD: +4.81%
Fit statistics				
Number of observations (number of respondents)			8,735 (2,039)	
F-test (33, 2006)			10.92	
Prob > F			0.00	

1 The multinomial logit model estimated under the assumption that AVs and SAVs are
2 available and affordable shed some interesting inferences. Table 16 shows the estimated
3 coefficients for this scenario. SAVs seem to be a dominating choice for business travel as
4 compared to the other modes as well as personal travel. Distance seems to only play a vital part in
5 deciding to choose to fly. Current vehicle ownership does indicate that one may be less interested
6 in AVs and SAVs, however, this is still a competing mode choice when other factors come into
7 play. Older people still seem to prefer the private car as the most preferred alternative with AVs
8 as their next choice, when everything else is constant. Having a current driver's license also deters
9 people from using these automated modes. Regardless of the household's income bracket, there
10 seems to be wide consensus in favoring SAVs as they are expected to turn out to be the most
11 affordable alternative.

Table 16: Model Estimation for Future Mode Choice in Long-Distance Travel with AVs and SAVs

Multinomial Logit Model			
Alternatives (Base Case – Private Car)	AVs	SAVs	Airplane
Independent Variables	Coefficient (T-stat)	Coefficient (T-stat)	Coefficient (T-stat)

Table 16: Model Estimation for Future Mode Choice in Long-Distance Travel with AVs and SAVs

Constant	1.79 (1.67)	-0.48 (-0.34)	1.92 (1.49)
Trip Type – Personal?	(base)		
– Business?	-0.03 (-0.15)	1.23 (4.83)	0.56 (3.22)
– Recreation?	-0.06 (0.78)	0.15 (0.86)	0.16 (1.94)
Distance: 100 – 500 miles	(base)		
> 500 miles	0.10 (0.86)	0.05 (0.29)	1.55 (10.45)
Household owns 1 vehicle?	-0.84 (-1.23)	-0.36 (-0.45)	0.20 (0.27)
2 vehicles?	-1.27 (-1.85)	-0.24 (-0.28)	-0.21 (-0.27)
3 vehicles?	-0.65 (-0.88)	0.41 (0.44)	-0.26 (-0.31)
4+ vehicles?	-0.72 (-0.83)	0.26 (0.26)	-0.80 (-0.91)
Household size equal to 2?	0.91 (2.21)	0.42 (0.74)	-0.37 (-0.79)
equal to 3?	0.12 (0.21)	-0.23 (-0.29)	-0.01 (-0.01)
equal to 4+?	-0.25 (-0.33)	-0.51 (-0.48)	-0.21 (-0.31)
Household workers equal to 1?	-0.45 (-1.20)	-0.97 (-1.82)	-0.97 (-2.29)
equal to 2?	-0.30 (-0.69)	-0.32 (-0.49)	-0.12 (-0.25)
equal to 3?	-0.59 (-0.84)	-1.40 (-1.61)	-0.94 (-1.30)
equal to 4+?	0.75 (0.60)	-0.72 (-0.46)	0.07 (0.05)
Age of respondent (in years)	-0.02 (-2.14)	-0.03 (-1.92)	-0.03 (-2.63)
Have U.S. driver's license?	-2.41 (-3.85)	-2.26 (-3.30)	-1.88 (-2.31)
Caucasian?	-0.26 (-0.81)	-1.01 (-2.41)	-0.75 (-2.12)
Children in the household: 1 child?	0.50 (1.05)	0.90 (1.48)	-0.96 (-2.07)
2 children?	1.35 (1.75)	0.89 (0.86)	-0.68 (-1.01)
3 children?	2.30 (2.42)	1.87 (1.59)	0.21 (0.23)
4+ children?	-0.43 (-0.37)	0.19 (0.15)	-1.10 (-1.27)
Household income: < \$20,000	0.78 (1.06)	1.75 (1.35)	0.34 (0.29)
Or < \$30,000	0.94 (1.27)	3.21 (2.63)	-0.21 (-0.22)
Or < \$40,000	0.69 (1.00)	2.98 (2.48)	0.22 (0.25)
Or < \$50,000	0.20 (0.32)	2.37 (2.04)	0.79 (0.90)
Or < \$60,000	1.76 (2.32)	4.84 (3.83)	0.88 (0.90)
Or < \$75,000	1.35 (1.87)	1.75 (1.42)	1.43 (1.53)
Or < \$100,000	0.83 (1.17)	3.72 (3.16)	1.50 (1.60)
Or < \$125,000	1.51 (2.20)	3.75 (3.27)	2.03 (2.23)
Or < \$150,000	1.62 (1.99)	3.10 (2.50)	2.30 (2.29)
Or < \$200,000	1.74 (2.22)	2.41 (1.87)	2.29 (2.50)
Or > \$200,000	1.41 (1.72)	2.60 (2.04)	2.11 (2.08)
Has attended some college?	0.23 (0.80)	0.89 (2.12)	0.75 (2.61)
Currently working at least part-time?	1.52 (3.07)	1.34 (2.02)	1.36 (2.34)
Single?	0.49 (2.17)	0.12 (0.37)	0.17 (0.65)
Population density (per square mile)	0.2E-4 (0.65)	0.5E-4 (1.24)	0.4E-4 (1.53)
Employment density (per square mile)	-0.5E-4 (-0.96)	-0.1E-4 (-1.06)	-0.8E-4 (-1.59)
Fit statistics			

Table 16: Model Estimation for Future Mode Choice in Long-Distance Travel with AVs and SAVs

Number of observations (number of respondents)		9,257 (2,005)
F-test (114, 1891)		5.74
Prob > F		0.00

1
2 In this case, the expected change in mode shares for all the modes discussed above is
3 calculated. This is done by identifying the expected value of the mode share at the new mean value
4 of the covariate. This helps see the practical effect of each covariate on future mode share. Table
5 17 shows the percentage change in mode-shares with respect to the previously determined share
6 and gives an idea of the impact of each of the covariates. As evaluated from the coefficients
7 previously, the absence of children may have a deep impact in choosing to fly compared to the
8 other modes for LD travel. There may be a 67% increase in SAVs' mode-share mainly due to
9 business travel. Absence of vehicle in the household also seems to favor use of AVs for future LD
10 travel. Households with few (up to 3) children may and significant number of workers prefer AVs
11 for their LD travel and this could be directly from high total household income. Interest in SAVs
12 is spread out through all income groups while results suggest that some income brackets may not
13 use SAVs for their LD needs.

Table 17: Covariate Elasticities for Future Mode Choice in Long-Distance Travel

Independent Variables	Change in Mode Share		
	AVs	SAVs	Airplane
Trip Type – Personal?	+3.84%	-24.96%	-7.22%
– Business?	-22.15%	+67.41%	+11.91%
– Recreation?	-5.01%	-16.40%	+1.43%
Distance: 100 – 500 miles	+19.53%	+24.46%	-38.74%
> 500 miles	-18.62%	-22.56%	+37.34%
Household owns 0 vehicles?	+43.60%	-10.43%	-18.83%
1 vehicle?	+2.08%	-31.03%	+12.20%
2 vehicles?	-15.35%	+1.82%	+4.84%
3 vehicles?	+14.32%	+51.67%	-18.32%
4+ vehicles?	+22.59%	+51.75%	-37.60%
Household size equal to 1?	-8.90%	+8.43%	+11.65%
equal to 2?	+33.38%	+22.20%	-27.20%
equal to 3?	-14.94%	-13.82%	+14.08%
equal to 4+?	-22.72%	-20.15%	+10.60%
Household workers equal to 0?	+0.61%	+33.71%	+8.97%
equal to 1?	+6.23%	-11.91%	-17.88%
equal to 2?	-10.77%	+11.72%	+14.82%
equal to 3?	+1.96%	-37.25%	-12.84%
equal to 4+?	+50.29%	-44.93%	-6.80%

Table 17: Covariate Elasticities for Future Mode Choice in Long-Distance Travel

Age of respondent (in years)	+1SD: -10.49%	-11.84%	-8.01%
	-1SD: +9.47%	-7.97%	+4.60%
Have U.S. driver's license?	Y: -5.47%	-3.45%	-0.22%
	N: +57.88%	+50.56%	-7.35%
Caucasian?	Y: +5.92%	-22.51%	-8.83%
	N: -6.31%	+32.34%	+13.96%
No child in the household	-17.73%	-23.61%	+19.81%
Children in the household: 1 child?	+23.66%	+65.69%	-39.38%
2 children?	+64.14%	+23.49%	-43.47%
3 children?	+83.96%	+38.39%	-39.40%
4+ children?	-31.94%	+36.73%	-14.44%
Household income: < \$20,000	+14.55%	-53.05%	-29.39%
Or < \$30,000	+23.18%	+56.66%	-54.99%
Or < \$40,000	-3.97%	+45.38%	-32.73%
Or < \$50,000	-32.27%	-32.00%	+6.72%
Or < \$60,000	+23.35%	+196.60%	-44.63%
Or < \$75,000	+22.17%	-77.55%	+6.73%
Or < \$100,000	-23.53%	+44.52%	+17.40%
Or < \$125,000	-5.78%	+6.78%	+30.00%
Or < \$150,000	-4.64%	-51.50%	+45.19%
Or < \$200,000	+5.64%	-76.17%	+43.47%
Or > \$200,000	-8.94%	-61.88%	+44.25%
Has attended some college?	Y: -3.13%	+13.49%	+7.77%
	N: +9.88%	-27.15%	-16.67%
Currently working at least part-time?	Y: +54.87%	+13.29%	-8.15%
	N: -8.89%	-8.12%	+0.62%
Single?	Y: -40.26%	-7.50%	+21.73%
	N: +21.98%	-0.54%	-16.15%
Population density (per square mile)	+1SD: -5.41%	+20.62%	+10.06%
	-1SD: +1.27%	-7.28%	-5.04%
Employment density (per square mile)	+1SD: -1.82%	-15.68%	-9.44%
	-1SD: -0.53%	+9.10%	+2.07%

1

2 **CONCLUSIONS**

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

1 Americans appear apprehensive about using AVs, with Texans more willing to employ such
2 automation. More than 65% of survey respondents have not yet used a ride-hailing service, and
3 only 25% of users had shared their ride (with an unknown traveler) in such vehicles. Most of these
4 people (i.e., prior ride-hailing users) are not comfortable sending their children in a ride-hailing
5 vehicle by themselves.

6 Ride-sharing preferences among adults were assessed in detail here. A hurdle model to predict this
7 WTP during the day suggests that added travel time, respondent age and gender, household size
8 and income (between \$75k and \$125k), disability and driver's license status, and presence of a
9 worker in the home are important predictors of one being WTP to share one's ride. After clearing
10 this criteria, added travel time was not statistically significant, but variables of household size and
11 vehicle ownership, respondent age, race, and land use variables were valuable predictors. Practical
12 significance was analyzed by changing the average respondent's covariate. WTP for DRS may
13 decrease by 26% as the population ages, however, a reduction in driver licensure can increase it
14 by 38%. Higher employment densities or household incomes may increase WTP by 21% and 26%,
15 respectively. Few respondents appear willing to use DRS at night, but those who are willing state
16 an average WTP of \$0.87 per mile.

17 Higher levels of concern emerge when privacy is the focus of a survey question, rather than one
18 among many potential issues to be selected by a respondent. A hurdle model was used to estimate
19 the WTP for anonymizing location while using AVs. Age, number of children in the household,
20 vehicle ownership and income were major predictors in determining one's WTP. They are against
21 targeted advertising (based on their trip coordinates, for example), but comfortable with their data
22 being used for policing, community surveillance, and/or traffic management decisions.

23 Crash ethics were also investigated, using three targeted questions based on different crash
24 scenarios. The largest single share of Americans (54%) feel that any AV, when having no choice
25 but to crash into one or more pedestrians (or other vehicles, in a related question [with 31% of
26 respondents]) should not change its trajectory (to select a different pedestrian or vehicle to crash
27 into), even if the current trajectory does not minimize overall harm. Avoiding children was also a
28 popular response, but not the top response. AV manufacturers were dominantly (60.9% of
29 respondents) deemed fully responsible for all such crashes.

30 Americans expect much of their long-distance travel (for trips over 50 miles, one-way) to shift
31 toward AVs and SAVs. For example, nearly 50% of trips between 50 and 500 miles (one-way) are
32 expected to eventually take place in an AV or SAVs, and this is considerably lower than LaMondia
33 *et al.*'s (2016) prediction of around 55%, on average for these ranges. Airplanes are expected to
34 deliver a major share of business trips (more than currently stated by respondents, perhaps due to
35 some future-optimism bias about affordability). A binary logit model estimated that income played
36 a vital role in determining mode choice in the current scenario without AVs or SAVs. A
37 multinomial logit for long-distance mode choices in the presence of affordable AVs and SAVs,
38 suggests that Americans prefer SAVs, irrespective of their household's income, *ceteris paribus*.
39 Some business travel under 500 miles is also expected to be completed using SAVs. Older people
40 are estimated to prefer to use their own vehicles, now and in the future. Shifts in mode splits were
41 also examined. For example, SAV share for long-distance trips rises by 67% when the average
42 long-distance traveler is traveling for business. Work-centric households (more than average
43 number of workers in the household) may prefer to own AVs more than other households. Middle-
44 class households may be greatly inclined towards SAVs (196% increase in share if the average
45 respondent was earning between \$75k and \$120k).

46 These results suggest that Americans are not yet very confident about AV use, but expect to
47 develop heavy usage levels. WTP, demand levels, perception and public opinion are helpful to
48 transportation planners and policymakers, technologists and vehicle manufacturers, fleet managers
49 and system operators, as well as airlines, land developers, attorneys, insurers, and the tourism

1 industry. Privacy in trip-making is a concern, with some respondents WTP to anonymize location
2 data. Perceptions of ethics in crash choices should facilitate design of anti-crash algorithms. The
3 aviation sector may wish to adjust its investments and future marketing strategies in response to
4 changes in market share for long-distance travel. Regardless of position, preferences will evolve,
5 as designs are rolled out and experience by more and more people, around the world. Regular
6 survey efforts help nations and regions, companies and public agencies, better prepare for the
7 coming paradigm shifts, hopefully with equity, environment, and efficiency in mind. The
8 limitation to keep the survey relatively brief meant that some other new innovative questions were
9 removed before final dissemination. New surveys can inquire about new AV and SAV design,
10 when there will be no need of a driver. Additionally, in the realm of ride-sharing, acceptable
11 waiting times can be assessed instead of forcing a pre-determined waiting time on the respondent
12 for WTP questions.

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18 REFERENCES

- 19 Abraham, H., Lee, C., Brady, S., Fitzgerald, C., Mehler, B., Reimer, B. and Coughlin, J., 2016.
20 Autonomous Vehicles, Trust, and Driving Alternatives: A survey of consumer preferences. MIT
21 AgeLab White Paper (2016-6). AgeLab, Massachusetts Institute of Technology. Retrieved from:
22 [http://agelab.mit.edu/files/publications/2016_6_Autonomous_Vehicles_Consumer_Preferences.p](http://agelab.mit.edu/files/publications/2016_6_Autonomous_Vehicles_Consumer_Preferences.pdf)
23 [df](http://agelab.mit.edu/files/publications/2016_6_Autonomous_Vehicles_Consumer_Preferences.pdf) (July 20, 2017).
- 24 Agatz, Niels, Erera, Alan, Savelsbergh, Martin and Wang, Xing., 2011. Dynamic ride-sharing: A
25 simulation study in metro Atlanta. *Procedia Social and Behavioral Sciences* 17: 532-550.
- 26 Bansal, Prateek and Kockelman, Kara., 2016. Are We Ready to Embrace Connected & Self-
27 Driving Vehicles? A Case Study of Texans. *Transportation* 44: 1-35.
- 28 Bansal, Prateek and Kockelman, Kara., 2017. Forecasting Americans' Long-Term Adoption of
29 Connected and Autonomous Vehicle Technologies. *Transportation Research Part A* 95: 49-63.
- 30 Bischoff, J., Soeffker, N. and Maciejewski, M., 2016. A framework for agent based simulation of
31 demand responsive transport systems. Proceedings in the International Conference on Operations
32 Research, Hamburg, Germany. Retrieved from: <http://dx.doi.org/10.14279/depositonce-5760>
33 (June 30, 2017).
- 34 Bonnefon, J., Shariff, A. and Rahwan, I., 2016. The social dilemma of autonomous vehicles.
35 *Science* 352(6293): 1573-1576.
- 36 Cragg, J., 1971. Some Statistical Models for Limited Dependent Variables with Application to
37 the Demand for Durable Goods. *Econometrica* 39(5): 829-844.
- 38 Deloitte., 2014. Global Automotive Consumer Study Exploring consumers' mobility choices and
39 transportation decisions. Retrieved from:
40 <https://www.autonews.com/assets/PDF/CA92618116.PDF> (July 10, 2017). Fagnant, Daniel J. and
41 Kockelman, Kara M., 2016. Dynamic ride-sharing and fleet sizing for a system of shared
42 autonomous vehicles. In *Transportation* 45: 1-16.

- 1 Farhan, Javed and Chen, T. Donna. Impact of Ridesharing on Operational Efficiency of Shared
2 Autonomous Electric Vehicle Fleet., 2017. Under review for publication in *Transportation*
3 *Research Part C: Emerging Technologies*.
- 4 Fleetwood, Janet., 2017. Public Health, Ethics, and Autonomous Vehicles. *American Journal of*
5 *Public Health* 107(4): 532-537.
- 6 Goodall, Noah J., 2017. From Trolleys to Risk: Models for Ethical Autonomous Driving.
7 *American Journal of Public Health* 107(4): 496.
- 8 Jenkins, Ryan., 2016. Autonomous Vehicle Ethics & Law – Toward an Overlapping Consensus.
9 A New America Foundation Report. Retrieved from: [https://na-](https://na-production.s3.amazonaws.com/documents/AV-Ethics-Law.pdf)
10 [production.s3.amazonaws.com/documents/AV-Ethics-Law.pdf](https://na-production.s3.amazonaws.com/documents/AV-Ethics-Law.pdf) (July 10, 2017).
- 11 Kelly Blue Book., 2016. Future Autonomous Vehicle Driver Study – September 2016. Retrieved
12 from:
13 [https://mediaroom.kbb.com/download/Kelley+Blue+Book+Future+Autonomous+Vehicle+Drive](https://mediaroom.kbb.com/download/Kelley+Blue+Book+Future+Autonomous+Vehicle+Driver+Study+-+FINAL.pdf)
14 [r+Study+-+FINAL.pdf](https://mediaroom.kbb.com/download/Kelley+Blue+Book+Future+Autonomous+Vehicle+Driver+Study+-+FINAL.pdf) (July 10, 2017).
- 15 Krueger, Rico, Rashidi, Taha, and Rose, John., 2016. Preferences for shared autonomous
16 vehicles. *Transportation Research Part C* (69): 343-355.
- 17 LaMondia, J.J., Fagnant, D.J., Qu, H., Barrett, J. and Kockelman, K., 2016. Shifts in Long-
18 Distance Travel Mode Due to Automated Vehicles: Statewide Mode-Shift Simulation Experiment
19 and Travel Survey Analysis. *Transportation Research Record* (2566): 1-11.
- 20 Lee C., Ward C., Raue M., D'Ambrosio L., Coughlin J., 2017. Age Differences in Acceptance of
21 Self-Driving Cars: A Survey of Perceptions and Attitudes. Proceedings in the 3rd International
22 Conference on Human Aspects of IT for the Aged Population, Vancouver, Canada. Retrieved
23 from: https://link.springer.com/chapter/10.1007/978-3-319-58530-7_1 (July 20, 2017).
- 24 PUMS (Public Use Microdata Sample) (2011-2015) United State Census Bureau: American
25 Community Survey. Retrieved from: [https://www.census.gov/programs-](https://www.census.gov/programs-surveys/acs/data/pums.html)
26 [surveys/acs/data/pums.html](https://www.census.gov/programs-surveys/acs/data/pums.html) (June 10, 2017).
- 27 Quarles, N., and Kockelman, K., 2017. Americans' Plans for Acquiring and Using Electric,
28 Shared and Self-Driving Vehicles. Under review for publication in *Transportation*, and available
29 at http://www.cae.utexas.edu/prof/kockelman/public_html/TRB18surveyFleetEvolution.pdf
- 30 San Francisco Municipal Transportation Agency., 2015. Travel Decisions Survey 2015 –
31 Summary Report, San Francisco. Retrieved from:
32 [https://www.sfmta.com/sites/default/files/reports/2016/Travel%20Decision%20Survey%202015](https://www.sfmta.com/sites/default/files/reports/2016/Travel%20Decision%20Survey%202015%20Report_Accessible.pdf)
33 [%20Report_Accessible.pdf](https://www.sfmta.com/sites/default/files/reports/2016/Travel%20Decision%20Survey%202015%20Report_Accessible.pdf) (June 30, 2017).
- 34 Schoettle, B. and Sivak, M., 2014. A Survey of Public Opinion About Autonomous and Self-
35 Driving Vehicles in the U.S., the U.K., and Australia. University of Michigan, Technical Report
36 No. UMTRI-2014-21. Retrieved from: <https://deepblue.lib.umich.edu/handle/2027.42/108384>
37 (June 30, 2017).
- 38 Schoettle, B. and Sivak, M., 2016. Motorists Preferences for Different Levels of Vehicle
39 Automation – 2016. University of Michigan, Technical Report No. SWT-2016-8. Retrieved
40 from: <http://umich.edu/~umtriswt/PDF/SWT-2016-8.pdf> (July 20, 2017).
- 41 Sommer, K., 2013. Continental Mobility Study 2013. Continental AG. Retrieved from:
42 [https://www.continental-](https://www.continental-corporation.com/resource/blob/7380/6cddc571cd3d3b5cacad279fe0d1a00c1/mobistud-2013-dl-data.pdf)
43 [corporation.com/resource/blob/7380/6cddc571cd3d3b5cacad279fe0d1a00c1/mobistud-2013-dl-](https://www.continental-corporation.com/resource/blob/7380/6cddc571cd3d3b5cacad279fe0d1a00c1/mobistud-2013-dl-data.pdf)
44 [data.pdf](https://www.continental-corporation.com/resource/blob/7380/6cddc571cd3d3b5cacad279fe0d1a00c1/mobistud-2013-dl-data.pdf) (June 30, 2017).

- 1 StataCorp, 2015. *Stata Statistical Software: Release 14*. College Station, TX: StataCorp LP.
- 2 Vujanic, A., and Unkefer, H., 2011. Embedded software consumer pulse survey. Accenture
- 3 Research. Retrieved from:
- 4 <https://newsroom.accenture.com/content/1101/files/EmbeddedSoftwareOverall.pdf> (June 30,
- 5 2017).