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Spatial Modeling of Electric Vehicle Ownership across Texas and A Simulation-based Framework to Predict Americans' Adoption of Autonomous Vehicle Technologies

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Spatial Modeling of Electric Vehicle Ownership across Texas and A Simulation-based Framework to Predict Americans' Adoption of Autonomous Vehicle Technologies

by

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To

Consciousness

Acknowledgements

In my opinion, success is not about achieving milestones; rather it is about a fraction of well-wishers in our social networks who want to see us achieving even more desperately than ourselves. I would like to take this opportunity express my gratitude to all the well-wishers.

My advisor, Dr. Kara Kockelman, taught me to juggle many things at once efficiently and push myself beyond limits. I am grateful to her for constant research guidance and spending invaluable time in providing quick and comprehensive feedback on my write-ups; I feel privileged to have worked with such a pleasant, energetic, down-to-earth, and passionate mentor. During my graduate research, I was lucky to have worked with Dr. Stephen Boyles, the finest teacher I ever had. I am obliged to him for his friendly suggestions amidst tough decisions, and inviting me to all his stress-buster potluck dinners. I sincerely thank Dr. Geetam Tiwari (my undergraduate advisor) for her constant guidance and introducing me to this wonderful research community.

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Preface

This thesis is divided into four loosely-connected parts, all of which focus on modeling and understanding Americans' current and future adoption of smart and emerging vehicle technologies.

The *First part* estimates hybrid electric vehicle (HEV) ownership rates and average fuel economy across Texas's census tracts using state-of-art multivariate spatial models (estimated using Bayesian Markov Chain Monte Carlo [MCMC] sampling) (Bansal et al. 2015a). Thanks to the NSF Industry-University Research Center for supporting this research, to Texas A&M University's Prof. Steve Puller for providing access to the vehicle registration data, and to the Texas Department of Motor Vehicles for permitting this access. A paper based on this research was accepted for publication in *Transportation Research Record* and was presented at the Transportation Research Board's 94th annual meeting in January 2015, with Kara Kockelman and Yiyi Wang as co-authors.

The remaining three parts of this thesis are based on the results of three stated-preference surveys (which obtained opinions and other information from 3,602 Americans in Spring 2014 and Summer 2015) and are closely linked, since all draw insights about Americans' opinions (e.g., adoption timings, and concerns and benefits) of connected and autonomous vehicle (CAV) technologies at the national, state (Texas), and regional levels. Thanks to the Texas Department of Transportation (TxDOT) for supporting nation- and state-level studies.

More specifically, the *second part* develops a simulation-based framework to predict Americans' long-term (2015 to 2045) adoption rates of CAV technologies under temporal variations in willingness to pay (WTP) and technology prices, and National Highway Traffic Safety Administration's (NHTSA) current and future regulations (Bansal and Kockelman 2015a). This research resulted in a second paper, which is under review for publication in *Transportation Research Part A*, with Kara Kockelman as co-author.

The t*hird and fourth parts* facilitate a variety of perception and attitude analyses of Texans and Austinites, respectively, using various econometric models. The key response variables include respondents' WTP for Level 3 AVs, Level 4 AVs, and CVs; adoption rates of shared AVs (SAVs) under different pricing scenarios; adoption timing of CAV technologies; home location decisions after AVs and SAVs become common travel modes; and support for road-tolling policies (to avoid excessive demand from easier travel). The *fourth part* of this thesis contains the details of a paper under review for publication in *Transportation Research Part C*, with Kara Kockelman and Amit Singh as co-authors (Bansal et al. 2015b); while a publishable manuscript based on the third part is under preparation with Kara Kockelman (Bansal and Kockelman 2015b).

Abstract

Spatial Modeling of Electric Vehicle Ownership across Texas and A Simulation-based Framework to Predict Americans' Adoption of Autonomous Vehicle Technologies

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The University of Texas at Austin, 2015

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This thesis is divided into four parts. The *first part* investigates the impact of built-environment and demographic attributes on adoption rates of hybrid electric vehicles and more fuel-efficient vehicles. To allow for spatial autocorrelation (across census tracts) in unobserved components of tract-level vehicle counts, as well as cross-response correlation (both spatial and aspatial), vehicle counts by vehicle type and fuel economy levels were estimated using bivariate and trivariate Poisson-lognormal conditional autoregressive models. Fuel-efficient-vehicle ownership rates were found to rise with household income, resident's education levels, and the share of male residents, and fall in the presence of larger household sizes and higher job densities.

In the *second part*, a fleet evolution framework was designed to simulate Americans' long-term (year 2015 to 2045) adoption of connected and autonomous vehicle (CAV) technologies under eight different scenarios based on 5% and 10% annual drops in technology prices; 0%, 5%, and 10% annual increments in Americans'

willingness to pay (WTP) for such technologies; and U.S. (federal) regulations regarding technology adoption. A survey was designed and disseminated to obtain 2,167 Americans' behavioral data and preferences; and those data were used for the various simulations. The survey results indicate that Americans' average WTP to add connectivity and Level 3 and Level 4 automation are $67, $2,438, and $5,857, respectively. The simulation results predict that 24.8% (assuming 5% annual drop in technology prices and constant WTP) to 87.2% (assuming 10% annual drop in technology prices and 10% annual rise in WTP) of the Americans' privately owned vehicles will be fully automated by 2045.

The final two parts of this multi-part thesis summarizes findings of two separate surveys, polling 1,088 Texans and 347 Austinites, respectively, to understand their opinions on CAV technologies and strategies. Ordered probit, interval regression, and other econometric models of human behavior were estimated to understand the impact of demographics, built environment features, and other attributes on Austinites' and Texans' WTP to add CAV technologies to their vehicles, as well as the adoption rates of shared AVs (SAVs) under different pricing scenarios, adoption-timing's dependence on friends' adoption rates, and home-location decisions after AVs and SAVs become common modes of transport. The Texas study's results indicate that those who support speed regulation strategies and have higher household income are estimated to pay more, on average, for all CAV technologies, but older and more experienced licensed drivers tend to place lower value on these technologies, everything else constant. The Austin study's results indicate that higher-income technology-savvy males, living in urban areas and those who have experienced more crashes, have a higher WTP for the new technologies. Moreover, Texans and Austinites share many common perceptions and expect fewer crashes to be the primary benefit of AVs, with equipment failures being their top concern.

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PART 1: HYBRID ELECTRIC VEHICLE OWNERSHIP AND FUEL ECONOMY ACROSS TEXAS: AN APPLICATION OF SPATIAL MODEL

Chapter 1: Introduction and Background[1]

Many worry about the world's continuing reliance on petroleum as a transportation fuel, with various air quality impacts and energy security issues. Fuel economy is a salient feature of automobiles, and fuel-efficient hybrid electric vehicles (HEVs) are achieving some marketplace success (Keith 2012, Chen et al. 2014, Paul et al. 2011, Dijk et al. 2013). For example, 495,000 HEVs were sold in the United States in 2013, with over 1.5 million sold worldwide (EVs Roll 2014). Only 96,000 plug-in EVs (PEVs) were sold in the US in 2013, which includes 47,700 battery-only EVs (EVs Roll 2014), so the PEV future is less certain. Since market success depends on consumer response, understanding the factors that affect purchase and use of more fuel efficient and electric vehicles becomes crucial for sales and use forecasts, as well as energy and environmental policies (Koo et al. 2012).

While EV sales (including both HEVs and PEVs) have risen considerably in the United States over the past decade, high adoption rates tend to concentrate in a relatively few cities and neighborhoods. In the case of Texas, Figure 1.1 shows how HEV ownership rates (per 1,000 registered light-duty vehicles [LDVs]) concentrate in the state's biggest cities/regions: San Antonio, Austin, Dallas-Ft. Worth, and Houston. (Since almost no PEVs were registered in Texas in year 2010 [according to the vehicle decoder used on the DMV database], only HEV counts were non-negligible in the 2010 Texas

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[1] A paper based on this research was accepted for publication in *Transportation Research Record* and presented at the Transportation Research Board's 94th annual meeting in January, 2015, with Kara Kockelman and Yiyi Wang as co-authors (Bansal et al. 2015a). Both co-authors supervised this research.

data sets, and thus analyzed separately from conventional vehicles here.) Within these regions, spatial variation is striking (Figure 1.1). Understanding of the factors behind such variations provides direction for policymaking, planning, production, and marketing.

One reason for the clustering in HEV ownership rates is presumably spatial correlation in local government incentives and marketing, demographics, and land use patterns (Kodjak 2012, Chen et al. 2014). Another reason for the clustering relates to the theory of social contagion, with consumers more likely to buy EVs if they see them regularly, on nearby roads, in neighbor's driveways, and being driven by their friends and colleagues (Axsen and Kurani 2011). Positive contagion feedbacks can intensify to create adoption inhomogeneity at different scales.

This study's first two models employ a multivariate conditional autoregressive (MCAR) specification (as developed by Wang and Kockelman [2013] and applied in Chen et al. [2014]) to understand many of the factors responsible for adoption rates of HEVs and other classes (based on fuel economy) of LDVs across Texas' major cities, while recognizing correlations that emerge over space across vehicle ownership types. The study's bivariate model (Model 1) estimates counts of HEVs vs. non-HEV passenger vehicles in each of the four largest counties of Texas' top 4 regions. The trivariate model (Model 2) examines tract-level registration numbers in each of 3 fuel-economy-based vehicle classes (fuel efficient [>25 mi/gal], regular [15 to 25 mi/gal], and fuel inefficient [≤15 mi/gal]). A third model (Model 3) is of average fuel economy, across all census tracts of Texas, and so relies on a continuous-response spatial error model for spatial autocorrelation (Wall 2004, Kissling et al. 2008, and Anselin 1988).

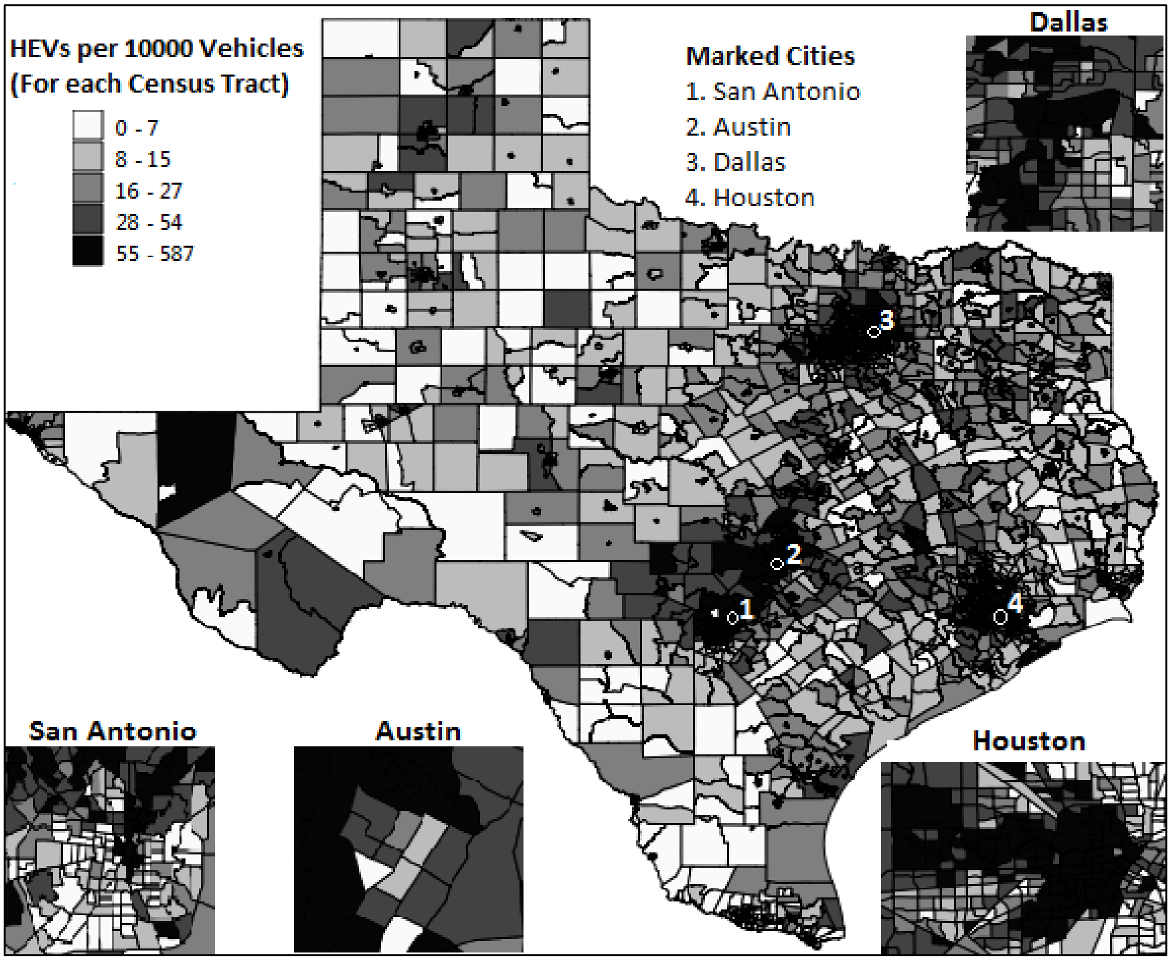

Figure 1.1: HEV Adoption Rates in Year 2010 across Texas Census Tracts (using Texas Department of Motor Vehicles registration data, 2010)

1.1 Discrete Choice Models for HEV Ownership

Several researchers have developed choice models to identify key factors encouraging EV and other vehicle purchases. For example, Li et al. (2013) used a bivariate probit model to find that consumers with environmentally-relevant information (from the Internet or friends) were more likely to purchase HEVs than flex-fuel vehicles, whereas males, those driving more miles, and those registered as Republicans were less inclined. He et al.'s (2012) hierarchical choice model analysis of the U.S. National Household Travel Survey (NHTS) 2009 and Vehicle Quality Survey data found that those primarily making local trips (versus highway-based trips) and those with higher education have a more positive attitude toward buying an HEV. Caulfield's (2010) survey of an Irish car company's new customers suggest that preferences depend significantly on vehicle price, reliability, safety, and fuel costs.

1.2 Willingness to Pay for HEVs and Fuel Economy

Liu (2014) estimated that U.S. consumers are willing to pay, on average, from \$960 to \$1720 more (depending on their income category) for HEVs, which is lower than an HEV's typical price premium. Jenn et al. (2013) estimated that the Energy Policy Act of 2005 caused a 4.6% increase in U.S. HEV sales for every \$1000 incentive provided (per HEV). Liu (2014) concluded that offering \$1000 and \$3000 tax savings would increase U.S. HEV sales by 4% and over 13% respectively. Using a 5% discount rate, Tuttle and Kockelman (2012) estimated that gas prices above approximately \$5.90, \$5.00, and \$3.75 per gallon are estimated to make the Leaf, Volt, and Prius-PHEV (as offered in year 2011) more financially attractive, respectively, than their conventional counterparts - without any credits. In Musti and Kockelman's (2011) survey, 76% of Austinites (with sample weighted to reflect true local population) stated that fuel economy lies in their top three criteria for vehicle purchase, and 56% claimed they would consider purchasing a plug-in HEV if it were to cost \$6,000 more than its internal combustion counterpart (vs. just 36% of all *U.S.* respondents in Paul et al.'s [2011] follow-up survey).

Auto purchases by individuals are arguably not as rational as those by fleet managers, who have the time and expertise to do rigorous net present valuations. To understand Americans' willingness to pay for fuel savings, Greene et al. (2013) surveyed 1000 US households four times: in 2004, 2011, 2012 and 2013. Each time, they estimated that US car buyers expect fuel economy savings to payback up-front vehicle costs in just 3 years, suggesting consumer myopia, significant risk aversion (to car loss, rather than gas price increases), and/or a very high personal discount rate (on a vehicle's future benefits). They argue that accuracy of fuel economy information is extremely important, because its uncertainty leads loss-averse consumers to significantly undervalue fuel savings. In some contrast, Koo et al. (2012) calibrated mixed logit and mixed multiple discrete continuous extreme value (MDCEV) models for Koreans' recent vehicle purchases, and concluded that Koreans tend to care most about fuel economy. Axsen and Kurani (2013) found that new-vehicle buyers in California prefer HEVs and PEVs, not only because of their functional benefits (e.g., lowered gasoline use and emissions), but also due to their image association (with intelligence, responsibility, and support for the environment and national energy security).

1.3 Spatial Models for HEV Ownership

Very few studies have explored spatial variations and neighborhood effects in HEV adoption rates. Keith et al. (2012) developed a spatial diffusion model to understand the reasons behind high-adoption clusters of the Toyota Prius HEV across the United States. For greatest impact or sales increases, they concluded that HEV adoption should be incentivized in regions already exhibiting strong adoption. Chen et al. (2014) employed an MCAR model to anticipate LDV registration counts of the Prius HEV, other EVs, and conventional (internal combustion) vehicles across 1000 census block groups in the city of Philadelphia. They found that more central/core zones and those with more higher-income households have higher EV ownership rates, and that spatial correlations exist in unobserved terms (not controlled for by their set of eleven covariates).

As noted above, most studies on vehicle choice are disaggregated in nature. Few studies have explored spatial variations in adoption rates or have worked with complete samples. This study employs rigorous and behaviorally plausible spatial models to better illuminate overall factors that affect fuel economy choices and adoption rates of HEVs and other LDVs across much of the U.S.'s second largest state.

Chapter 2: Data Acquisition and Summary Statistics

2.1 Data Acquisition and Transformation

This study uses the Texas Department of Motor Vehicles' (DMV's) vehicle registration counts for year 2010. This database includes all registered vehicles in Texas, from cement trucks and combines harvesters to passenger cars and motorized scooters. The fuel type and fuel economy of vehicles were added to the DMV data using a vehicle identification number (VIN) decoder, as purchased by Texas A&M University's Dr. Steve Puller, and able to decode all vehicles with model years newer than 1980. To provide anonymity to households, the final data set shows only total vehicle counts by fuel type (hybrid, diesel, flex fuel, and gasoline) and fuel economy (miles per gallon, MI/GAL) across Texas census tracts.

Out of the state's 22.81 million registered-vehicle records, the LDV decoder was able to match 17.35M vehicles to fuel information, leaving 5.19 million unmatched due to an early model year (before 1981) or commercial-vehicle status (heavy- and medium-duty trucks and agricultural equipment that sometimes runs on roadways. The VIN decoder also placed all plug-in HEVs and battery EVs in the "unknown" category. For another 205,630 vehicle records (0.90% of the database), fuel type was identified but not census tract, and for another 63,296 vehicle records (0.28% of registered vehicles), neither tract nor fuel information was matched.

Puller's team coded the 2010 vehicles to the U.S. census tract system of year 2000 (in order to map to census income data). For consistency in covariate timing, the count data were transferred to the year 2010's system using a census tract relationship file (US Census Bureau 2010). Texas' tract counts in years 2000 and 2010 were 4388 and 5265, respectively; so 2010 tracts are somewhat smaller, reflecting a higher year 2010 state population (25.1M in 2010 versus 20.8M in 2000). 2200 of the year-2000 census tracts remained intact, while the rest split or merged. Vehicle counts in modified tracts come from a population-weighted average of year-2000 person counts.

2.2 Response Variables

This study relies on three models of vehicle type and fuel economy. The first two are multivariate models for vehicle counts by type: Model 1 is a bivariate model with HEV and non-HEV counts (in each census tract) as the response variables. Model 2 is a trivariate model with vehicle counts in three fuel economy bins as the response variables. Model 2's three fuel economy levels are determined by thresholds one standard deviation (4.81 mi/gal) away from the mean fuel economy (19.30 mi/gal) for the state's entire LDV fleet. After rounding those thresholds, the bins' cut points are 15 mi/gal and 25 mi/gal. The vehicles falling into these low, medium and high fuel economy categories are referred to here as "fuel inefficient", "regular" (fuel economy), and "fuel efficient" vehicles, respectively. Finally, Model 3 relies on a single, continuous response variable, average fuel economy per tract, along with a spatial error model (Cressie 1993 and Anselin 1988). Figure 2.1 shows a histogram of fuel economy across Texas's LDV fleet, as registered in the year 2010.

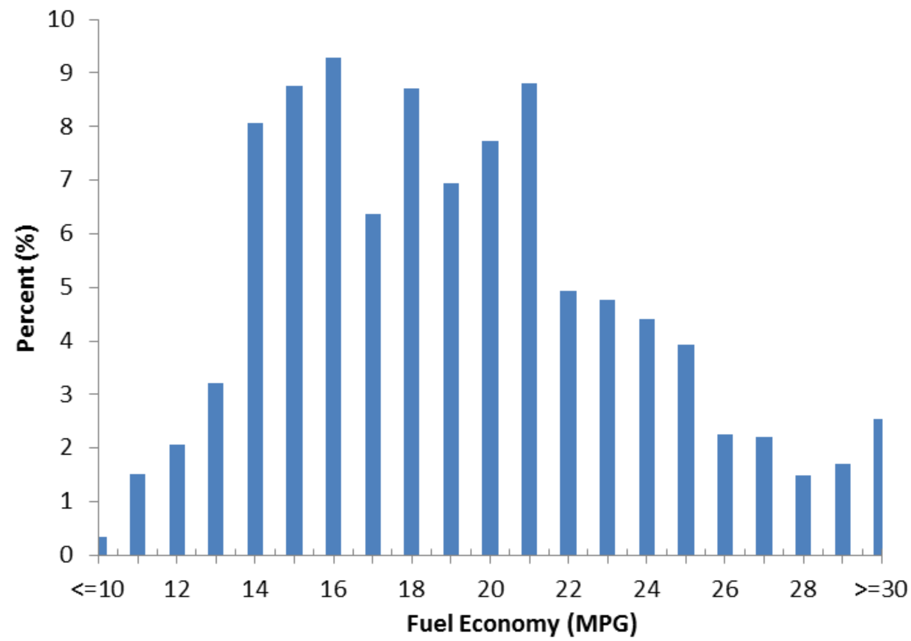

Figure 2.1: Histogram of Fuel Economy across All Registered Light-duty Vehicles in Texas (2010)

2.3 SUMMARY STATISTICS

The model's covariates mainly capture census-tract-level demographic attributes, like average age, gender, race, household size, education, population density, number of commuting workers, and income. These tract-level covariates come from the U.S. Census of Population 2010 database (which offers a complete sample of many variables) and the 2010 American Community Survey (ACS) estimates (which samples a share of households every year, for a host of additional variables). 5,188 Census tracts (out of Texas's 5,265 tracts) offered complete data for the aforementioned covariates and response variables. Jobs density and land use balance[2] variables were also obtained for Travis County from the Capital Area Metropolitan Planning Organization. Table 2.1

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[2] Land use balance was computed using the following entropy term (from Cervero and Kockelman [1997]): $-\left(\sum_{k=1}^{4} p_k \log p_k\right)/\ln(4)$, where p_k is the proportion of land use type k (including residential, commercial, office, and industry uses) in the tract. An equal or uniform balance (with 25% of land falling into each of the four categories) yields the maximum entropy value of 1.

provides summary statistics of all census tract level variables. Since vehicle counts should (in theory) scale with population counts (e.g., one may expect a doubling in vehicle registrations when tract population is doubled), tract population variable is used an exposure variable for the count models. Due to this scaling, many covariates are controlled for as fractions, rather than as counts.

Table 2.1: Model Variables' Summary Statistics at Census Tract Level across Texas (2010)

Variable Name	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Dependent Variables (Model 1)					
# Hybrid EVs in tract	16.56	9.50	21.88	0	500
# Non-Hybrid LDVs in tract	3,320	2,956	2,122	74	50,993
Dependent Variables (Model 2)					
# Fuel efficient LDVs (≥25 mi/gal)	470.3	403	523.2	0	22,715
# Regular LDVs (≥15 mi/gal & <25 mi/gal)	2,358	2,103	1,454	43	26,003
# Fuel inefficient vehicles (<15 mi/gal)	507.4	450	292.0	15	3,429
Dependent Variables (Model 3)					
Average fuel economy of tract's LDVs (mi/gal)	19.23	19.19	0.825	16.70	23.07
Covariates (all Texas Census tracts)					
Total population of tract (exposure variable)	4,841	4,457	2,450	85	34,354
Fraction of population 16 years old or younger	0.236	0.238	0.059	0	0.515
Median age (years)	35.18	34.40	6.562	14.90	71.30
Male fraction	0.495	0.492	0.033	0.313	0.987
African American fraction	0.119	0.058	0.164	0	0.963
Average household size (# persons)	2.77	2.73	0.50	1.31	4.84
Fraction of pop. with Bachelor's degree or higher	0.248	0.188	0.191	0	0.893
Population density (per square mile)	3,103	2,451	3,288	0.1271	68,892
Fraction of workers commuting by driving	0.783	0.800	0.091	0.118	1
Mean household income (dollars per year, in 2010)	66,416	57,637	36,273	12,821	445,620
Fraction of households with income over $100,000	0.186	0.135	0.166	0	1
Fraction of families below poverty level	0.144	0.111	0.124	0	1
Additional Covariates (for Travis County tracts)					
Land use balance	0.645	0.712	0.229	0.036	0.988
Employment density (jobs per square mile)	1200.1	704.2	1379.2	1.5	7655.2

Chapter 3: Model Specification and Estimation

Since Models 1 and 2 have bivariate and trivariate count values as response vectors, and the data are highly spatial in nature, Wang and Kockelman's (2013) Poisson-lognormal MCAR model specification was applied here. This model quantifies the contributions of tract-level heterogeneity, spatial dependence in error terms (unobserved attributes) for the same count type, and aspatial and spatially-lagged correlations across response types.

3.1 Bivariate Conditional Autoregressive Model

The first stage of bivariate CAR specification can be expressed as a Poisson process:

$$y_{ik} \sim \text{Poisson}(\lambda_{ik}) \tag{1}$$

where y_{ik} is the observed vehicle count by vehicle type (k = 1 for HEVs and k = 2 for conventional passenger vehicles) for the i^{th} census tract of Texas, and the expected vehicle counts(λ_{ik}) for each vehicle type and tract are defined in the second step, as follows:

$$\ln(\lambda_{ik}) = \ln(E_{ik}) + \boldsymbol{x}_i{}'\boldsymbol{\beta_k} + \phi_{ik} + u_i \tag{2}$$

where E_{ik} is an exposure term (population of each census tract in this case), $\boldsymbol{x_i}$ is a column vector of covariates for the i^{th} census tract, $\boldsymbol{\beta}_k$ is a column vector of parameters specific to vehicle type *k*, ϕ_{ik} indicates the MCAR model's spatial random effects (shown in Equation 3), and u_i captures tract-specific heterogeneity or latent variations (not explained by spatial effects). The random error term, ϕ_{ik} captures spatial dependence, as measured by ρ_1 and ρ_2 in Equations 4 and 5, which are specific to each vehicle type. The model's overall covariance structure allows for aspatial and spatially-lagged correlations between error terms (unobserved effects) for the two vehicle types, as shown in Equations 3 to 5.

$$\begin{pmatrix} \boldsymbol{\phi_1} \\ \boldsymbol{\phi_2} \end{pmatrix} \sim N\left(\begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{12}' & \boldsymbol{\Sigma}_{22} \end{pmatrix}\right) \tag{3}$$

where $\boldsymbol{\phi}_k$ is a *n* by 1 vector containing the spatial random effects across *n* census tracts for vehicle type *k*, and $\boldsymbol{\Sigma}_{kl}$ is the matrix of covariance terms across vehicle types *k* and *l*. The spatial MCAR structure was constructed using a series of conditional distributions, expressed as follows:

$$\boldsymbol{\phi}_2 \sim N(\mathbf{0}, [(\boldsymbol{D} - \rho_2 \boldsymbol{W})\tau_2]^{-1}) \tag{4}$$

$$\boldsymbol{\phi}_1 | \boldsymbol{\phi}_2 \sim N(\boldsymbol{A}\boldsymbol{\phi}_2, [(\boldsymbol{D} - \rho_1 \boldsymbol{W})\tau_1]^{-1}) \tag{5}$$

where $\boldsymbol{D} = diag(m_i)$, with m_i denoting the number of neighbors for the i^{th} census tract, $\boldsymbol{W}$ is a second-order contiguity matrix (where all $W_{ii} = 0$, while $W_{ij} = 1$ if *i* and *j* share a common border and W_{ik} =1 if *j* and *k* share a common border, else $W_{ij} = 0$), τ_i is a scaling parameter for the covariance matrix of the i^{th} vehicle type, and ρ_i is a measure of spatial autocorrelation in error terms for counts of the i^{th} vehicle type (across tracts), Finally, $\boldsymbol{A}$ is a transformation matrix, which can be written as follows:

$$\boldsymbol{A} = \eta_0 \boldsymbol{I} + \eta_1 \boldsymbol{W} \tag{6}$$

Using Equations 5 and 6, $\boldsymbol{\phi_1}$'s conditional mean can be written as follows:

$$E(\boldsymbol{\phi}_1 | \boldsymbol{\phi}_2) = (\eta_0 \boldsymbol{I} + \eta_1 \boldsymbol{W})\boldsymbol{\phi}_2 \tag{7}$$

3.2 TRIVARIATE CONDITIONAL AUTOREGRESSIVE MODEL

The trivariate CAR model has spatial random effects listed as $\boldsymbol{\phi} = \left(\boldsymbol{\phi}'_1, \boldsymbol{\phi}'_2, \boldsymbol{\phi}'_3\right)'$. The sequence of conditional distributions is the key in estimation of MCAR models. The marginal distribution of $\boldsymbol{\phi}_3$ can be written as $p(\boldsymbol{\phi}_3) \sim \boldsymbol{N}(0, [\tau_3(\mathbf{D} - \rho_3\mathbf{W})]^{-1})$, and the marginal distribution of $(\boldsymbol{\phi}_2, \boldsymbol{\phi}_3)$ can be obtained from the full distribution, as follows:

$$\begin{pmatrix} \boldsymbol{\phi}_2 \\ \boldsymbol{\phi}_3 \end{pmatrix} \sim N\left(\begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \begin{bmatrix} \Sigma_{22} & \Sigma_{23} \\ \Sigma'_{23} & \Sigma_{33} \end{bmatrix}\right) \tag{8}$$

where $\boldsymbol{\phi}_2 | \boldsymbol{\phi}_3 \sim N(\mathrm{A}_{23}\boldsymbol{\phi}_3,\ [(\boldsymbol{D} - \rho_2\boldsymbol{W})\tau_2]^{-1})$ and A_{23} describes the aspatial and the spatially-lagged correlation between the fuel economy levels 2 and 3 (i.e., $\mathrm{A}_{23} = \eta_{0,23}I + \eta_{1,23}W$). Moreover, $\boldsymbol{\phi}_1 | \boldsymbol{\phi}_2, \boldsymbol{\phi}_3 \sim N(\mathrm{A}_{13}\boldsymbol{\phi}_3 + \mathrm{A}_{12}\boldsymbol{\phi}_2,\ [(\boldsymbol{D} - \rho_1\boldsymbol{W})\tau_1]^{-1})$ and, A_{13} and A_{12} capture the aspatial and spatially-lagged correlation across fuel economy levels 1 and 3, and 1 and 2, respectively, i.e. $\mathrm{A}_{13} = \eta_{0,13}I + \eta_{1,13}W$ and $\mathrm{A}_{12} = \eta_{0,12}I + \eta_{1,12}W$.

3.3 MCAR MODEL ESTIMATION

Vehicle-count models 1 and 2 were implemented using a combination of R programming language and WinBUGS software. The model parameters were estimated using Bayesian Markov Chain Monte Carlo (MCMC) sampling techniques. Due to the complex nature of this multivariate sampling with spatial autocorrelation, it was not possible to estimate model parameters for all 5188 census tracts across Texas simultaneously. Moreover, spatial effects in vehicle ownership patterns are also expected to die out over miles of separation (after controlling for demographics and other local attributes). Therefore, the most populous counties in the state's 4 most populous regions were used to deliver a suite of separate models. These comprise the counties of Harris (with 780 tracts covering the central Houston region), Dallas (526 tracts), Bexar (361 tracts in central San Antonio), and Travis[3] (215 tracts in central Austin).

3.4 SPATIAL-ERROR MODEL SPECIFICATION AND ESTIMATION

As noted earlier, a relatively standard spatial-error specification (Cressie 1993, Anselin 1988) was employed for Model 3, in order to predict the average fuel economy of LDVs in each tract. Thanks to the continuous nature of the response variable (average fuel economy), sample size is not an issue, and this model was estimable using all census tracts across Texas (n = 5,188). Model 3's parameters were estimated using classical maximum likelihood estimation techniques, via the R programming language.

[3] Models 1 and 2 were calibrated for Travis County using the additional covariates of employment density and land use balance.

Chapter 4: Estimation Results

4.1 Model 1 Results, for HEV and Non-HEV Counts

To evaluate the performance between spatial and aspatial models, goodness-of-fit statistics of three model specifications were compared using each of the four counties' data sets. The first model shown is the original Poisson lognormal MCAR specification, the most behaviorally flexible (and complicated) of the three. The second is a Poisson lognormal CAR (η_0 and η_1 =0), which allows for spatial dependence but removes cross-correlation among vehicle types. The last model tested uses a Poisson-lognormal multivariate specification ($\rho_1, \rho_2, and\, \eta_1 = 0$), which ignores spatial dependence but still permits cross-correlation. Table 4.1's comparison of average log-likelihood values (after convergence of the Bayesian MCMC sample chains) and deviance information criterion (DIC) values of these models suggest that the original model, with an MCAR specification, outperformed the simpler models (Table 4.1), as expected.

Table 4.1 also shows Model 1's parameter estimates for all four counties. The directions and magnitudes of all covariates' effects on vehicle ownership rates (per person) are consistent across counties, with a few exceptions (mainly in cases of non-statistically and non-practically significant variables). Most variables are statistically significant (with pseudo t-statistic more than 1.64 or less than -1.64), and those that are most practically significant (as judged by highly elastic behaviors) have their estimates shown in bold. All elasticity estimates were generated by increasing each covariate's value by 1% in each census tract and obtaining the average of proportional changes in the county's total/overall vehicle ownership rate predictions (for each of the two vehicle classes).

The presence of children (persons under 17 years of age) exhibits a positive[4] (and statistically significant) association with non-HEV ownership rates in Bexar and Travis counties. A plausible interpretation is that greater shares of children indicates the presence of more families, which tend to favor cars of larger size, and most larger vehicles are not available in hybrid design. Similarly, median age of tract residents positively affects both vehicle ownership rates (HEV and non-HEV) across all counties, with the exception of HEV ownership rates in San Antonio's Bexar County. This effect is very practically significant in Dallas County, where one-percent increase in the median age of population (in each tract) is predicted to come with an average 1.07 percent increase in HEV ownership rates (per person).

A high share of males leads to higher ownership rates (and counts), regardless of vehicle type and location. Evidently, males prefer to own more cars (and trucks), and have a preference for hybridization (perhaps because males drive more than females, on average [according to the 2009 NHTS], and so can harness more HEV fuel savings). Their effects are substantial: the average increase in HEV ownership rates following a one-percent increase in each tract's fraction of males are 3.62, 3.98, 2.43, and 1.99 percentage points - across Bexar, Dallas, Harris, and Travis counties, respectively. (The elasticities for non-HEV ownership rates are 1.25, 1.68, 0.78, and 3.37, respectively.).

Race and ethnicity were controlled for in these regressions, with the share of African Americans having a statistically significant effect. This race variable predicted lower vehicle ownership rates in all four counties, for both vehicle types (except in the case of Harris County's non-HEV ownership, where it was not statistically significant).

[4] The presence of children is negatively associated with non-HEV ownership rates is Dallas and Harris counties, but it is not statistically significant.

In Dallas and Harris Counties, African Americans 21.5 and 19.5 percent of the population, respectively, and offer significant HEV ownership impacts in these counties.

Average household size is found to have significant (both statistically and practically[5]) negative effect on HEV ownership levels. As alluded to above, larger households may have seek to buy larger vehicles than is available in hybrid versions, to accommodate children, friends, pets, vacation baggage for recreational trips, and large shopping items (Turrentine and Kurani 2007). When hybrid versions are available, they are often much more expensive: e.g., the Chevrolet Tahoe hybrid is the most cost-effective SUV of its size, but $13,000 costlier than the conventional Tahoe (Wiesendelder 2013).

The share of population with higher education (i.e., at least a Bachelor's degree) has a consistently positive and statistically significant (but not very practically significant) impact on HEV ownership rates. Well-educated individuals know more about environmental issues, and new technologies; and owning a less environmentally damaging vehicle may allay some of their concerns (Egbue and Long 2012, Axsen and Kurani 2013). Moreover, HEV ownership can symbolize and communicate to others their personal values, as related to environmental awareness (Heffner et al. 2007).

While a host of other variables, like parking prices, transit provision, jobs access, and local land use balance would be valuable to have in these models, they are not available at the Census tract level across Texas. However, population density may proxy for several of these built environment and access attributes (Potoglou and Kanaroglou 2008), and is available at the tract level. As expected, population density has a negative and statistically significant impact on HEV and non-HEV ownership levels (Chu 2002).

[5] The effect of average household size on HEV ownership rates of Travis County is also negative, but neither statistically nor practically significant.

Elasticity magnitudes are relatively high for the population density variable, in several cases (e.g., -0.72 for Austin HEVs and -0.61 for Dallas HEVs), suggesting that this is a key variable (as confirmed by Chen et al.'s [2014]).

As expected, the share of workers commuting to work by driving has a positive (and statistically significant) impact on both vehicle ownership rates in Bexar and Harris counties[6], but was estimated to be practically significant only for HEV ownership rates in San Antonio's Bexar County. It is surprising that average household income shows no significant impacts (except for non-HEV ownership rates in Bexar County), perhaps due to the confounding effects of other income-related variables in the model. For example, the fraction of high-income households (those with annual income over $100,000) is positively associated with greater HEV ownership and lower non-HEV ownership rates. These results may reflect the tendency of high-income households to choose pricier vehicles over more (short-term) economical ones, rather than purchasing more vehicles (Prevedouros and Schofer 1992). Related to this, the tract-wide share of families living below the U.S. poverty level negatively[7] affects vehicle ownership rates of both types, but mostly significant for HEV ownership rates. Perhaps, financially disadvantaged people cannot afford HEVs' relatively higher prices (Gallagher and Muehlegger 2011), though fuel savings may offset such expenses over time (Tuttle and Kockelman 2012).

The positive and statistically significant coefficient on the land use balance (entropy) variables suggests higher vehicle ownership rates (per person) in Travis County's (Austin's) more mixed-use locations, per capita, perhaps due to smaller households sizes with fewer children and relatively high income per capita in such

[6] The share of workers commuting by car and has an unexpected negative impact on the HEV ownership rates of Dallas County, but it is not practically or statistically significant.

[7] The share of families below poverty level is exceptionally positively affecting the non-HEV ownership rates of Dallas, but it is not statistically significant.

locations. Moreover, employment density is negatively associated with vehicle ownership rates in Travis County, as expected (due to a tendency for higher land values and relative scarcity of low-cost parking in more jobs-rich locations). However, Travis County's jobs-density variable is only statistically significant for HEV ownership rates.

The second-order autocorrelation coefficients, ρ_1 and ρ_2, seek to account for missing variables that affect vehicle ownership rates and vary over space, such as parking availability and congestion. The autocorrelation coefficients for both types are highly significant, but coefficients for HEV ownership rates (ρ_1 = {0.79, 0.81, 0.76, 0.74}, with t-stats. = {8.1, 9.2, 8.5, 7.1} for Bexar, Dallas, Harris, and Travis counties, respectively) are remarkably and consistently high across all counties, suggesting social contagion effects (Keith 2012, Lane and Potter 2007) and a high spatial clustering of HEVs (Chen et al. 2014).

The extremely high (and very statistically significant) aspatial correlations (within a census tract) between HEV and non-HEV adoption rates in each county are also of interest, and not unexpected (with η_0 = {0.58, 0.77, 0.66, 0.60}, and pseudo t-statistics = {4.1, 7.2, 3.8, 5.1}). In other words, high HEV and non-HEV adoption rates tend to co-exist in individual census tracts due to missing factors, which vary in the space. Interestingly, spatially-lagged cross-response correlation coefficient (η_1) estimates are quite low across all counties, suggesting that HEV adoption rates are not much affected by the non-HEV adoption rates in neighboring census tracts, which appears very reasonable.

Table 4.1: Model 2's Parameter Estimates for Vehicle Ownership Counts at Different Fuel Economy Levels, using an MCAR Specification

Model Specification		**San Antonio** (Bexar County, n=361 tracts)		**Dallas** (Dallas County, n=526 tracts)		**Houston** (Harris County, n=780 tracts)		**Austin** (Travis County, n=215 tracts)	
		DIC	Average log likelihood	DIC	Average log likelihood	DIC	Average log likelihood	DIC	Average log likelihood
Poisson Log-Normal MCAR		6331	-5720	9139	-8247	13549	-12284	4033	-3632
Poisson Log-Normal CAR (η_0 & $\eta_1 = 0$)		6952	-6199	9828	-8641	14790	-13183	4725	-4101
Poisson Log-Normal Multivariate (ρ_1, ρ_2& $\eta_1 = 0$)		7199	-6308	9967	-8835	14986	-13567	4802	-4285
Model 1's Parameter Estimates (using the Poisson-Lognormal MCAR specification)									
Variables	**Type**	**Mean estimate (t-stat.)**	**San Antonio elasticity**	**Mean estimate (t-stat.)**	**Dallas elasticity**	**Mean estimate (t-stat.)**	**Houston elasticity**	**Mean estimate (t-stat.)**	**Austin elasticity**
Constant	HEV (1)	-9.16 (-12.4)	-	-7.92 (-8.4)	-	-7.52 (-24.5)	-	-7.54 (-9.3)	
	Non-HEV (2)	-3.14 (-29.4)	-	-1.92 (-7.2)	-	-1.70 (-16.8)	-	-3.01 (-7.7)	
Fraction of population 16 years old or younger	1	2.77 (0.8)	0.652	1.75 (1.2)	0.216	2.34 (1.3)	0.564	1.05 (0.9)	0.126
	2	1.06 (2.5)	0.261	-1.34 (-1.4)	-0.124	-1.06 (-0.8)	-0.112	2.94 (3.04)	0.595
Median age of population (years)	1	-3.17E-03 (-0.6)	-0.121	2.88E-02 (3.8)	**1.075**	1.46E-02 (2.1)	0.374	2.48E-02 (2.2)	0.838
	2	1.41E-02 (4.2)	0.512	1.06E-02 (2.8)	0.363	8.14E-03 (2.4)	0.245	-7.95E-03 (-1.2)	-0.266
Male fraction	1	6.87 (7.2)	**3.621**	7.12 (6.5)	**3.982**	6.43 (7.3)	**2.435**	3.91 (2.6)	**1.994**

Table 4.1 (continued)

	2	2.45 (8.4)	**1.253**	3.21 (5.8)	**1.683**	1.56 (5.4)	0.789	6.56 (8.7)	**3.371**
African American fraction	1	-0.72 (-0.9)	-0.048	-1.28 (-5.2)	-0.224	-0.65 (-4.8)	-0.001	-2.64 (-3.5)	-0.219
	2	-0.62 (-2.0)	-0.046	-4.23E-02 (-0.4)	-0.008	4.12E-02 (0.5)	0.008	-1.39 (-1.8)	-0.115
Average household size	1	-0.85 (-4.4)	**-2.331**	-0.99 (-10.5)	**-2.456**	-0.75 (-10.6)	**-2.208**	-0.42 (-2.6)	-0.956
	2	-1.62E-02 (-0.4)	-0.045	7.36E-02 (1.5)	0.213	0.12 (6.1)	0.389	-0.47 (-3.1)	**-1.151**
Fraction of population with Bachelor's degree or higher	1	3.11 (2.3)	0.910	2.23 (3.2)	0.814	1.15 (4.1)	0.278	1.36 (3.1)	0.582
	2	0.12(0.8)	0.036	0.22 (1.1)	0.062	2.22E-02 (0.5)	0.005	-1.06 (-3.6)	-0.451
Population density (per square mile)	1	-3.15E-05 (-3.1)	-0.455	-5.31E-05 (-5.2)	-0.612	-1.23E-05 (-2.3)	-0.027	-7.94E-05 (-4.5)	-0.724
	2	-2.11E-05 (-3.7)	-.091	-3.12E-05 (-4.5)	-0.112	-1.06E-05 (-2.7)	-0.079	-5.69E-05 (-5.1)	-0.232
Fraction of workers commuting by driving	1	1.88 (2.5)	**2.214**	-0.73(-.7)	-0.626	0.81 (2.1)	0.105	0.36(0.6)	0.466
	2	1.12 (6.1)	0.867	0.28 (1.2)	0.112	0.55 (3.3)	0.521	0.98 (2.5)	0.715
Mean household income (dollars)	1	2.11E-06 (0.6)	0.115	-1.02E-06 (-0.8)	-.0718	7.82E-07 (0.5)	0.062	-1.44E-06 (-0.5)	-0.111
	2	4.11E-06 (2.1)	0.256	-8.11E-07 (-0.5)	-0.044	-7.18E-07 (-0.3)	-0.037	-2.41E-06 (-1.2)	-0.186
Fraction of households with income over $100,000	1	0.45 (0.7)	0.091	1.11 (2.1)	0.132	1.38 (3.8)	0.292	0.97 (1.1)	0.226

Table 4.1 (continued)

	2	-1.12 (-2.2)	-0.121	-0.56 (-1.8)	-0.097	-9.23E-02 (-0.2)	-0.045	-9.15E-02 (-0.7)	-0.025
Fraction of families below poverty level	1	-1.01 (-3.1)	-0.126	-1.25 (-2.8)	-0.278	-1.68 (-3.8)	-0.319	-0.26 (-0.5)	-0.032
	2	-8.15E-02 (-0.3)	-0.011	4.12E-02 (0.1)	0.007	-0.22 (-1.3)	-0.061	-0.68(-1.9)	-0.086
Land use balance	1	-	-	-	-	-	-	0.30 (1.8)	0.231
	2	-	-	-	-	-	-	0.44 (2.5)	0.303
Employment density	1	-	-	-	-	-	-	-6.88E-05 (-1.7)	-0.081
	2	-	-	-	-	-	-	-3.92E-05 (-0.8)	-0.043
η_0		0.58 (4.1)	-	0.77 (7.2)	-	0.66 (3.8)	-	0.60 (5.1)	-
η_1		0.21 (1.8)	-	.09 (1.6)	-	0.19 (1.2)	-	0.18 (2.2)	-
ρ_1		0.79 (8.1)	-	0.81 (9.2)	-	0.76 (8.5)	-	0.74 (7.1)	-
ρ_2		0.55 (6.2)	-	0.59 (4.2)	-	0.62 (5.1)	-	0.62 (5.9)	-

Notes: DIC is the deviance information criterion[8]. Highly elastic cases (|η| > 1.0) are shown in **bold**.

[8]The model with the smallest DIC is estimated to be the model that will best predict another sample data set with the same structure as that currently observed. $DIC = \overline{D} + P_D$, where $P_D$is effective number of parameters and $\overline{D}$ is posterior mean of deviance $D(\boldsymbol{\theta})$; $D(\boldsymbol{\theta}) = -2 \times loglikelihood + C$, where C is a constant that cancels across calculations and $\boldsymbol{\theta}$ is a vector of unknown parameters.

4.2 Model 2 Results, for Vehicle Counts by Fuel Economy Category

Table 4.2 shows Model 2's parameter estimates. Since most HEVs fall into the third ("fuel efficient") vehicle category, some Model 2 coefficients are quite consistent with those estimated for Model 1. The presence of children yields no significant effect on the adoption rates of fuel efficient and inefficient vehicles, but has a positive and statistically significant effect on adoption rates or counts of regular vehicles in two counties (for San Antonio and Austin locations). As in Model 1, higher (median) ages (of tract residents) and shares of males have significantly positive associations with all rates of vehicle ownership. Elasticity values of 1.10 to 2.17 (across the 4 counties) suggest that a higher share of males will have the greatest practical effect on the purchase of fuel-efficient vehicles. A higher tract share of African Americans and higher population density offer a negative association with vehicle ownership rates, regardless of fuel efficiency level, presumably for the same reasons discussed above, in the context of Model 1 results. Population density remains rather a key here, with elasticity magnitudes ranging from 0.099 to 0.332 (for the categories of fuel-inefficient vehicles in Houston and regular vehicles in Austin). Unlike many of the other covariates, density is a variable that almost has no bounds, and can vary by orders of magnitude in U.S. data sets; thus, its cumulative effects on ownership, vehicle choices, travel distances, and fuel use can be quite sizable.

Rising average household size is associated with lower ownership rates of fuel efficient vehicles and higher fuel-inefficient vehicle adoption rates across all counties. As suggested earlier, this may be attributed to larger households seeking more full-size vehicles (e.g., SUVs and minivans), which typically have fuel economy ratings below 25 mi/gal (U.S. Department of Energy 2014)[9]. As discussed earlier, for Model 1, higher education levels are positively associated with higher ownership of fuel efficient vehicles and lower rates of fuel-inefficient vehicles.

The share of workers that commute by driving has positive and significant effects on all three vehicle ownership rates in Bexar and Harris counties, as expected. (Dallas County has negative coefficient estimates, but it is statistically and practically insignificant.) While average household income is not a significant predictor, the share of high-income households has positive (and significant except in Travis County) effects on ownership of more efficient vehicles in all counties, with strongest responses for San Antonio's and Dallas' central counties (thanks to elasticity estimates of 0.37 and 0.14, respectively). As noted earlier, this underscores the fact that fuel-efficient vehicles tend to cost more than other vehicles and are more affordable for higher-income households (Collins 2013, Prevedouros and Schofer 1992). Moreover, using the Travis County model results, greater land use balance is associated with higher vehicle ownership rates (in a statistically significant way), while greater employment density is correlated with lower vehicle ownership rates (but this latter relationship is statistically significant only for rates of fuel-efficient vehicles).

As before, spatial autocorrelation values (ρ's) suggest that sizable spatial clustering patterns exist in ownership rates, across all vehicle types (Keith 2012, Lane and Potter 2007). Within the same census tract, correlation between fuel-efficient and regular-vehicle ownership rates (η_{012}) is not significant, but correlations between rates of fuel-efficient and inefficient ownership (η_{013}), and between rates of-fuel inefficient and regular vehicle ownership (η_{023}) are significant. Across census tracts, the spatially-

[9] Austin's Travis County yields the opposite sign on household size and education levels, but these estimates are not significant (and may come from the presence of many college-age students in Travis County, who reside in Travis County to attend U.T. Austin and other schools).

lagged cross-correlations for all response pairs are statistically insignificant and very low in magnitude, suggesting that levels of fuel efficient vehicles in one census tract are not appreciably affected by adoption rates of other types of vehicles in neighboring (first- and second-order contiguity) tracts.

Table 4.2: Model 2's Parameter Estimates for Vehicle Ownership Counts at Different Fuel Economy Levels, using an MCAR Specification

Variables	Type	**San Antonio** (Bexar County, n=361 tracts)		**Dallas** (Dallas County, n=526 tracts)		**Houston** (Harris County, n=780 tracts)		**Austin** (Travis County, n=215 tracts)	
		Mean (t-stat.)	**Elasticity**	**Mean (t-stat.)**	**Elasticity**	**Mean (t-stat.)**	**Elasticity**	**Mean (t-stat.)**	**Elasticity**
Constant	Fuel Efficient (1)	-3.82 (-5.7)	-	-2.37 (-3.6)	-	-2.84 (-5.3)	-	-3.11 (-3.2)	-
	Regular (2)	-2.41 (-4.5)	-	-1.77 (-3.4)	-	-2.08 (-6.3)	-	-4.42 (-3.1)	-
	Fuel Inefficient (3)	-4.60 (-8.6)	-	-4.31 (-7.7)	-	-4.24 (-11.4)	-	-5.76 (-8.1)	-
Fraction of population 16 years old or younger	1	2.46 (0.3)	0.593	1.20 (0.6)	0.287	0.52 (0.9)	0.126	0.29 (0.3)	0.062
	2	1.72 (3.9)	0.415	-0.34 (-0.6)	-0.0816	-0.77 (-0.4)	-0.188	0.81 (2.1)	0.163
	3	0.97 (0.6)	0.233	-2.64 (-0.9)	-0.625	-0.79 (-0.9)	-0.192	0.29 (0.4)	0.056
Median age of population (years)	1	-7.11E-03 (-0.3)	-0.242	2.61E-03 (2.5)	0.088	1.11E-02 (2.7)	0.707	1.14E-02 (3.2)	0.678
	2	6.98E-03 (1.6)	0.238	1.69E-02 (3.8)	0.574	1.26E-02 (4.4)	0.424	3.11E-02 (3.1)	0.715
	3	1.79E-02 (4.1)	0.613	1.43E-02 (5.0)	0.425	1.69E-02 (5.3)	0.569	1.53E-02 (3.9)	0.502
Male fraction	1	2.24 (2.7)	**1.101**	3.78 (4.4)	**1.893**	2.62 (3.6)	**1.551**	3.11 (2.3)	**2.178**
	2	1.56 (2.4)	0.872	2.56 (3.7)	**1.085**	1.51 (3.6)	0.858	3.67 (2.8)	**1.871**

Table 4.2 (continued)

	3	2.07 (3.1)	0.821	2.60 (3.5)	0.933	2.44 (5.2)	0.852	6.31 (4.2)	**1.562**
African American fraction	1	-1.06 (-4.4)	-0.098	-0.40 (-3.2)	-0.086	-8.44E-02 (-4.9)	-0.046	-1.62 (-3.3)	-0.134
	2	-0.72 (-3.8)	-0.053	-0.84 (-1.4)	-0.062	8.89E-02 (0.7)	0.017	-1.12 (-2.4)	-0.091
	3	-1.05 (-5.5)	-0.078	-0.71 (-1.5)	-0.065	-0.28 (-1.8)	-0.056	-0.68 (-2.6)	-0.061
Average household size	1	-0.21 (-2.5)	-0.592	-0.25 (-3.3)	-0.702	-0.29 (-2.7)	-0.813	-4.56E-02 (-0.6)	-0.121
	2	-4.08E-02 (-0.6)	-0.115	3.43E-03 (0.05)	0.009	5.57E-02 (0.7)	0.160	0.14 (1.5)	0.398
	3	0.15 (2.2)	0.425	0.26 (3.9)	0.740	0.15 (4.2)	0.450	0.52 (3.8)	**1.267**
Fraction of population with Bachelor's degree or higher	1	0.41 (2.4)	0.101	0.25 (3.9)	0.076	0.63 (3.4)	0.171	-7.89E-02 (-0.6)	-0.034
	2	0.33 (1.4)	0.079	0.27 (1.2)	0.075	-5.97E-02 (-0.5)	-0.016	-0.23 (-0.2)	-0.098
	3	-0.26 (-1.2)	-0.065	-0.69 (-2.8)	-0.198	-1.16 (-9.0)	-0.313	-0.89 (-2.1)	-0.212
Population density (per square mile)	1	-3.92E-05 (-4.4)	-0.157	-4.91E-05 (-8.5)	-0.261	-5.56E-05 (-2.1)	-0.283	-6.19E-05 (-9.2)	-0.291
	2	-4.53E-05 (-6.4)	-0.181	-4.38E-05 (-9.4)	-0.151	-7.12E-06 (-3.1)	-0.036	-8.31E-05 (-6.1)	-0.332
	3	-6.11E-05 (-8.4)	-0.241	-3.95E-05 (-7.9)	-0.178	-1.94E-05 (-7.4)	-0.099	-7.19E-05 (-7.8)	-0.306

Table 4.2 (continued)

Fraction of workers commuting by driving	1	1.50 (5.8)	0.812	-0.19 (-0.3)	-0.151	0.64 (3.5)	0.494	1.11 (1.3)	0.747
	2	0.98 (4.8)	0.775	-0.18 (-0.3)	-0.141	0.49 (4.4)	0.382	0.48 (0.9)	0.435
	3	0.53 (2.6)	0.422	3.11E-02 (0.1)	0.024	0.33 (2.6)	0.253	0.51 (1.5)	0.342
Mean household income (dollars)	1	7.71E-06 (1.4)	0.485	-2.72E-06 (-0.6)	-0.192	3.12E-06 (0.2)	0.226	- 5.78E-06 (-1.4)	-0.413
	2	3.71E-06 (1.6)	0.233	-2.85E-07 (-0.3)	-0.020	-2.19E-07 (-0.5)	-0.016	-3.67E-06 (-1.1)	-0.247
	3	3.09E-06 (2.2)	0.194	-4.03E-06 (-0.4)	-0.284	-3.37E-06 (-0.3)	-0.245	-1.98E-06 (-1.3)	-0.156
Fraction of households with income over $100,000	1	2.22 (4.9)	0.370	0.74 (2.9)	0.142	0.25 (4.7)	0.053	3.13E-02 (0.8)	0.008
	2	-1.21 (-3.4)	-0.202	-0.72 (-2.3)	-0.137	2.19E-02 (0.2)	0.004	-8.12E-02 (-0.1)	-0.023
	3	-0.82 (-2.3)	-0.137	-0.71 (-2.1)	-0.126	-1.43E-02 (-0.08)	-0.003	-0.91 (-1.5)	-0.167
Fraction of families below poverty level	1	-0.54 (-2.1)	-0.078	-0.84 (-3.2)	-0.129	-0.81 (-4.4)	-0.123	-0.33 (-0.4)	-0.042
	2	-0.44 (-3.1)	-0.064	3.81E-02 (0.2)	0.006	-0.30 (-2.6)	-0.046	-0.25 (-2.9)	-0.034
	3	-0.10 (-0.5)	-0.015	0.91 (4.1)	0.139	-0.10 (-0.8)	-0.016	0.16 (0.2)	0.025
Land use balance	1	-	-	-	-	-	-	0.21 (2.1)	0.322

Table 4.2 (continued)

	2	-	-	-	-	-	-	0.11 (2.9)	0.412
	3	-	-	-	-	-	-	0.34 (1.9)	0.335
Employment density	1	-	-	-	-	-	-	-3.32E-04 (-2.1)	-0.112
	2	-	-	-	-	-	-	-8.27E-05 (-0.9)	-0.063
	3	-	-	-	-	-	-	-6.11E-05 (-0.3)	-0.045
η_{012}		0.32 (1.4)	-	0.39 (1.4)	-	0.36 (1.3)	-	0.45 (1.6)	-
η_{013}		0.40 (2.0)	-	0.49 (4.1)	-	0.52 (3.9)	-	0.56 (4.1)	-
η_{023}		0.59 (2.9)	-	0.58 (5.0)	-	0.67 (3.6)	-	0.61 (3.6)	-
η_{112}		2.37E-02 (1.7)	-	8.94E-02 (1.9)	-	5.35E-02 (1.9)	-	5.25E-02 (2.8)	-
η_{113}		6.36E-02 (1.8)	-	0.15 (1.3)	-	0.10 (1.4)	-	0.31 (1.4)	-
η_{123}		0.13 (1.6)	-	0.16 (1.3)	-	0.11 (1.3)	-	0.18 (1.2)	-
ρ_1		0.75 (7.2)	-	0.89 (6.5)	-	0.88 (9.2)	-	0.71 (6.9)	-
ρ_2		0.55 (4.9)	-	0.73 (6.1)	-	0.61 (2.8)	-	0.61 (5.7)	-

Table 4.2 (continued)

ρ_3	0.67 (5.5)	-	0.82 (6.6)	-	0.63 (5.6)	-	0.59 (6.8)	-
Deviance information criterion (DIC)	11,238	-	16,322	-	24,453	-	6,655	-

Note: Highly elastic cases (|η| > 1.0) are shown in **bold**.

4.3 Model 3 Results, for Average Fuel Economy

Table 4.3 shows Model 3's parameter estimates across Texas tracts. It is important to note that a tract having more fuel efficient vehicles (per resident) can also have a lower overall/average fuel economy value, due to an even higher count of inefficient vehicles. Thus, the results of Models 2 and 3 are not directly comparable here.

Table 4.3's robust LM test results suggest that one can use either a spatial error or spatial lag model specification here. A spatial error model is generally more behaviorally defensible, however, since it implies that unobserved factors are creating the spatial autocorrelation in model residuals, while a spatial lag model implies that response values in one location are simultaneously affecting responses values in nearby locations. Moreover, Kissling and Carl (2008) found that the spatial error model outperformed the spatial lag model across 1080 simulated data sets. For these reasons, a spatial error dependence specification was employed here, for Model 3.

All factors in Model 3 are found to be statistically significant predictors of average fuel economy. Census tracts with higher shares of children, males, and lower-income households are predicted to have lower average fuel economy, whereas a higher fraction of African Americans, Bachelor's degree holders, workers commuting by driving, and high-income households come with higher tract-level fuel economy. Higher median age, household size, and income variables, along with lower population density, are associated with lower fuel economy. A very high practical magnitude (+0.943) and statistical significance (likelihood ratio test p-value of 0.000) for the autoregressive error coefficient implies the existence of high spatial correlation among missing variables that affect average fuel economy and vary over space (like jobs densities, land values, and distance to each region's CBD).

The small variation (σ = 0.825 mi/gal) in tract-level average fuel economy may be the primary reason behind very low elasticity values, so standardized coefficients were estimated[10]. These standardized coefficient values are much more telling than the elasticities: they suggest that educational attainment, age, income, and then household size (in that order) are the most practically significant among the covariates. Only educational attainment is associated with a practically significant and positive improvement in fuel economy; tract-level increases in median age, average income, and average household size work against this desirable feature, of a more environmentally sustainable fleet.

Table 4.3: Lagrange Multiplier Test Results and Model 3's Parameter Estimates for Average Fuel Economy (n = 5,188 tracts across Texas)

Robust LM Test	**LM Test Statistic**		**P-value**	
Error lag test	4480.6		0.000	
Dependent variable lag test	1050.1		0.000	
Model 3's Parameter Estimates				
Explanatory Variable	**Coef.**	**Std. Coef.**	**Z-value**	**Elasticity**
Intercept	21.74	-	137.8	-
Fraction of population 16 years old or younger	-1.232	-0.089	-6.7	-0.014
Median age (years)	-0.028	**-0.227**	-22.4	-0.052
Male fraction	-0.853	-0.035	-5.10	-0.022
African American fraction	0.681	0.136	14.0	0.004
Average household size (# persons)	-0.298	**-0.180**	-12.6	-0.042
Fraction of population with Bachelor's degree or higher	1.120	**0.259**	16.1	0.014
Population density (per square mile)	2.55E-05	0.102	12.6	0.004
Fraction of workers commuting by driving	0.199	0.022	3.2	0.008
Mean household income (dollars per year, in 2010)	-5.1E-06	**-0.225**	-13.8	-0.018
Fraction of households with income over $100,000	0.327	0.065	3.5	0.003
Fraction of families below poverty level	-0.443	-0.066	-7.3	-0.003
Simultaneous autoregressive error coefficient (λ)	0.943	-	140.2	-
Likelihood ratio test on λ	4673.2 (p-value = 0.000)			
Akaike information criterion (AIC)	3368.5 (vs. 8037.9 for OLS model)			

Note: Practically significant covariates have their standardized coefficients shown in **bold.**

[10] Standardized coefficients were estimated by multiplying each slope coefficient estimate by the standard deviation (SD) in the associated covariate (as shown in Table 2.1) and dividing by the SD on the response variable (tract-average fuel economy: SD = 0.825 mi/gal). This renders each "Std. Coef." dimensionless, as a metric of how many SDs in the response variable once can expect following a 1 SD change in the associated covariate.

Chapter 5: Conclusions

This study employed a Poisson-lognormal CAR model to anticipate tract-level counts of HEVs and non-HEVs, fuel efficient and inefficient vehicles across Texas' most populous cities, along with a spatial error model for average fuel economy across all Texas tracts. Model results identify demographic (including population density) factors that most affect HEV ownership rates, vehicle ownership by fuel economy categories, and the average fuel economy of registered LDVs in each tract.

Results of the count models suggest that household size, resident gender, household income, jobs density, and education levels are key predictors for HEV adoption rates and fuel economy choices, though average fuel economy does not vary much across tracts (with $\mu = 19.2$, and $\sigma = 0.82$ mi/gal). It appears that larger households tend to not purchase HEVs or other fuel efficient vehicles, presumably due to a preference for larger vehicles (e.g., SUVs and minivans [Kockelman and Zhao 2000]), and possibly due to higher up-front pricing of fuel-saving technologies. Higher population densities are associated with statistically significantly lower vehicle ownership rates (regardless of vehicle type), presumably due to better access options to destinations without a private vehicle and due to more parking challenges or costs. All three model specifications exhibit high (and statistically significant) spatial autocorrelations and local (within a tract) cross-response correlations in unobserved attributes (like concern for the environment, parking challenges, manufacturers' marketing campaigns, locations of vehicle dealerships, and access to neighbors and friends who already own HEVs and/or vehicles that enjoy higher fuel economy). While the Bayesian sampling methods and the MCAR model specification are not familiar techniques for many data analysts, neglect of such correlations can result in biased parameter estimates. The spatial error model is more accessible to a variety of potential users (and exists in various software programs); it also can handle much larger data sets (though it effectively requires a continuous response variable).

Although modeling vehicle-choice behavior at the level of individuals or households, with disaggregate data, can also prove quite informative for understanding HEV ownership, such data are obtained for small samples of the population, and only sporadically. (For example, typically 1 percent or fewer households in a region provide data for a regional household travel survey, which is undertaken every 5 to 10 years. In contrast, DMV records contain all registered vehicles, continuously in time.) This study demonstrates how one can use rigorous spatial modeling methods at the census tract or other levels to understand vehicle ownership choices and fuel economy relationships across counties and a large state.

Opportunities for future research in this area are many. For example, while it is often challenging to obtain tract level data of various land use, transit provision, and other relevant variables across a state like Texas, inclusion of such covariates will provide even more insight for planners, policy-makers, automobile manufacturers, and other interested readers. Access to count data on PEVs (as these become non-negligible), average vehicle age information, and other features of DMV databases will also inform these analyses, while helping chart a course for charging infrastructure investments and other decisions. Vehicle age is relevant, for example, because lower-income households are less likely to buy new vehicles, and so may be holding less fuel efficient vehicles as rising Corporate Average Fuel Economy standards ensure the nation's new-sales fleet becomes more efficient. This study also was able to estimate rather complex MCAR count models for only subsets of Texas tracts, due to computing limitations; advances in Bayesian estimation and software programming may eventually permit estimation of such models for much larger data sets.

While ownership of an HEV does not require special charging stations, larger power transformers, or very large batteries on board, their rising presence does affect future sales, of vehicles and gasoline, as well as state and federal gas tax receipts, air quality, and energy security. Since early adopters of HEVs are likely to be more sustainability-minded and technology savvy than others, on average; so their heavy presence in various neighborhoods may well be a strong signal for the early adoption and longer-term registration numbers of plug-in EVs in those same locations. Greater understanding of the factors causing spatial clustering in all EVs' adoption rates can help shape environmental policy, infrastructure planning, and vehicle marketing.

PART 2: FORECASTING AMERICANS' LONG-TERM ADOPTION OF CONNECTED AND AUTOMATION VEHICLE TECHNOLOGIES

Chapter 6: Introduction[11]

There is much excitement about the future of car travel. Hybrid-electric vehicles, plug-in electric vehicles, carsharing services, and on-demand taxis are all examples of recent technological and strategic advancements in the modes of automobile travel. However, the real vehicle market revolution is associated with the introduction of autonomous vehicles (AVs), connected vehicles (CVs), and connected-autonomous vehicles (CAVs). CAVs introduce all sorts of different benefits from dramatic reduction of crash rates and congestion to concerns about security, safety and privacy, and negative economic consequences associated with transition to vehicle automation (Schoettle and Sivak 2014, Fagnant and Kockelman 2015b). Therefore, despite all the hype about CAVs, there is much uncertainty about the future of automated travel.

Policymakers, industry professionals, and researchers would like to be sure that their decisions now correspond to some realistic vision about CAVs. U.S. National Highway Traffic Safety Administration (NHTSA) (2013) published preliminary policy guidelines about AVs, which indicate that policymakers need to understand the future of AVs in order to adjust the current policies. Automobile enterprises and investment banks need to know what technologies will be in demand and which corresponding industries have the greatest potential for rapid growth. Researchers need to allocate their resources in the most promising vehicle automation research areas. All this requires at least a broad understanding of the future of CAVs.

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[11] A paper based on this research is under review for publication in *Transportation Research Part A* (Bansal and Kockelman 2015a). Kara Kockelman is a co-author on the paper and she supervised the research.

Forecasting long-term CAV technologies' adoption is not easy: many demand- (willingness to pay [WTP]) and supply-side factors (technology prices) must be taken into account. Several researchers (Litman, 2015), private enterprises (e.g., Laslau et al. 2014, Mosquet et al. 2015), and industry enthusiasts (e.g., Rowe 2015, Hars 2014), have made different predictions about the CAV technologies' future adoption rates. However, these predictions are based on the extrapolation of trends associated with previous vehicle technologies, expert opinions, or forecasts of supply-side variables, with very little emphasis on the underlined assumptions behind these predictions. To the best of authors' knowledge, demand-side considerations, like WTP for these technologies and vehicle transaction decisions, and government's regulations about mandatory technology adoption[12] are not taken into account in the previous studies. Moreover, none of these studies have mechanism (except expert opinions) to anticipate the adoption of specific Level 1 and Level 2 automation technologies[13] (e.g., lane centering assistance and adaptive cruise control), and very few forecasting adoption of vehicle connectivity. This study aims at filling these gaps, since it will be up to consumers to decide whether to adopt certain technologies (even at lower prices) or to continue driving their current, non-autonomous vehicles (in case of no regulations).

To this end, this study proposes a simulation-based fleet evolution framework to forecast Americans' long-term (year 2015 to 2045) adoption of CAV technologies under eight-different scenarios based on: 5% and 10% annual drop in technology prices; 0%, 5%, and 10% annual increment in Americans' WTP; and NHTSA's current and probable

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[12] ESC has been mandated on all new passenger vehicles in the US since 2012 model year (NHTSA 2012). NHTSA is expected to require connectivity on all vehicles produced after year 2020 (Automotive Digest 2014).

[13] NHTSA (2013) defined five levels of automation. To state briefly, automation Levels 0, Level 1, Level 2, Level 3, and Level 4 imply no automation, function-specific automation, combined function automation, limited self-driving automation, and full self-driving automation, respectively.

regulations on mandatory adoption of electronic stability control (ESC) and vehicle connectivity. These simulations predict the proportions of vehicle with specific technology at the end of each year under these scenarios.

A survey was designed and disseminated to obtain 2,167 Americans' preferences (i.e., demand side variables); and those data were used in simulation framework. The survey investigated each respondent's household's current vehicle inventory, and each respondent's technology adoption, future vehicle transaction decisions, WTP for, and interest in CAV technologies, AV use with trip type, travel pattern, and demographics. To incorporate the impact of demographics and built-environment variables on vehicle transaction decision, logit models were developed; and those were also integrated into the proposed simulation framework. The following sections describe related studies, the survey and simulations design, summary statistics, modeling specifications, key findings, and conclusions.

Chapter 7: Literature Review

Forecasting long-term adoption of CAV technologies is a fairly new topic. One of the most cited studies about CAV adoption is by Litman (2015). Based on deployment and adoption of previous smart vehicle technologies (like automatic transmission and hybrid-electric drive), Litman forecasted that AVs are expected to constitute around 50% of vehicle sales, 30% of vehicles, and 40% of all vehicle travel by 2040. He argues that faster implementation would require "low- and middle-income motorists, who normally purchase used vehicles or cheaper new models to spend significantly more in order to purchase a new automobile with self-driving capability."

Consulting firms, investments banks, and other private enterprises published several reports with predictions about CAVs technologies' expected market penetrations. A team from Lux Research (Laslau et al. 2014) predicts that the market size for Level 2 and Level 3 automation technologies will account for up to $87 billion by 2030. However, they argue that Level 4 technology is likely to be emerging by that time and Level 3 automation will still be a premium option, which is expected account for only 8% of new car sales.

Boston Consulting Group (Mosquet, et al. 2015) analysts predict that Level 4 AVs' sales will reach $39 billion or about 10% of all new light-vehicle sales by 2035. Researchers from Citi GPS (2014) believe that the market for fully-autonomous vehicles could reach $40 billion by 2025. IHS (2014) experts anticipate self-driving vehicles' sales to hit nearly 12 million by 2035 (around 9% of global auto sales) and full automation of entire vehicle-fleet by 2045.

Analysts from Morgan Stanley (2013) predict that Level 3 self-driving vehicles will be omnipresent by 2020 to 2030, and Level 4 AVs by 2045 to 2055. They also estimate additional cost of Level 3 automation to reach around $6,000 by 2030 and $10,000 for Level 4 automation by 2045. RAND Corporation (Zmud et al. 2013) report predicts that 15% of the fleet will be autonomous by 2030. Fehr & Peers Transportation Consultants (Bierstedt et al. 2014) expect the 25% of vehicle fleet to be autonomous by 2035. ABI Research (2013) associates' estimations are even more optimistic, with the forecasted 50% of all new vehicle sales to be occupied by AVs by 2032.

Navigant research study (Alexander and Gartner 2014) predicts autonomous vehicles sales to reach around 18 million (or 75% of all light-duty vehicles) by 2035 in the U.S. IDTechEx (Harrop and Das, 2015) experts assess the number of self-driving capable cars to reach 8.5 million by 2035 in the U.S.

Experts and industry enthusiasts also presented their opinions on future driverless vehicle adoption rates. Rowe (2015) believes that Level 4 CAVs will be prohibited in the populous areas by 2025 to 2035, however, they are expected to be everywhere by 2050 to 2060 CAVs, with a safe and reliable technology. He quotes that "by about 2060, manual control of cars anywhere near civilization will come to be seen kind of the way texting and driving is seen today: dangerous, stupid and sociopathic".

On the very optimistic side of opinion spectrum, Hars (2014) believes that already by 2030, 90% of all trips will be happening in Level 4 Avs, and car ownership will decline to 20% in the U.S., due to projected popularity of SAVs. Alberto Broggi (Institute of Electrical and Electronics Engineers, 2012) is also very optimistic: he believes that up to 75% of all vehicles on the road will be autonomous by 2040.

However, some experts are not as optimistic about the driverless future. According to Steve Shladover, deputy director at UC Berkeley, AVs are still fifty or more years away (Hutton, 2014). Jack Opiola, President of D'Artagnan Consulting, believes that Level 4 AVs at urban congested city centers are a lifetime away and does not expect Level 4 AVs' commercialization in next 25 years (Litman 2014, and Stone 2015).

Most of other recent studies (Schoettle and Sivak 2014, Bansal et al. 2015b) are focused on understanding respondents' currently perceived benefits and concerns about and present WTP for CAV technologies, among many other opinion-based attributes. To authors' best knowledge, this study is the first one to forecast long-term evolution of CAVs' fleet considering demand (consumers' WTP) and supply (technology prices) side variables, and NHTSA's regulations on ESC and vehicle connectivity. A few vehicle simulation frameworks have been developed for forecasting market shares of alternative fuel vehicles in Austin (Mushti and Kockelman 2010) and U.S. (Paul et al. 2011). However, these models are not directly applicable to forecasting the long-term adoption of CAV technologies, but provide a basis for this new framework.

Chapter 8: Survey Design and Data Processing

8.1 Questionnaire Design and Data Acquisition

The team designed and disseminated a U.S.-wide survey in June 2015 using Qualtrics, a web-based survey tool. The Survey Sampling International's (SSI, an internationally recognized and highly professional survey firm) continuous panel of respondents served as the respondents for this survey. The Office of Research Support at The University of Texas at Austin processed this study and determined it as "Exempt" from Institutional Review Board[14] (IRB) review (protocol number: 2014-09-0078).

Exploring respondents' preferences for the adoption of emerging vehicle and transport technologies, the survey asked 58 questions, divided into 6 sections. The survey asked respondents about their household's current vehicle inventory (e.g., odometer reading and average miles traveled per year), vehicles sold in the past 10 years, future vehicle preferences (e.g., buying or selling a vehicle, or only adding technology to the existing vehicles), and WTP for various CAV technologies. Respondents were also asked for their opinions related to CAVs (e.g., comfort in allowing vehicle to transmit data to various agencies and the appropriate developers for Level 4 AVs), travel patterns (e.g., using AVs for the long-distance trips and increase in frequencies of long-distance trips due to AVs), and demographics.

8.2 Data Cleaning and Sample Correction

A total of 2,868 Americans (including 1,762 Texans) completed the survey. Respondents who completed the survey in less than 13 minutes were assumed to have not read questions thoroughly, and their responses were discarded. Certain other respondents

[14] IRB reviews research studies to minimize the risks for human subjects, ensure all subjects give their consent and receive full information about risks involved in the research, and promotes equity in human subject research.

were considered ineligible for further analysis: those younger than 18 years, reporting more workers or children than represented in the household size, having a very old car with all technologies, reporting the same distance of their home from various places (airport and city center, for example), and providing other combinations of conflicting answers. After removing the fast responses and conducting some sanity checks, 2,167 responses (including 1,364 Texans) remained eligible for further analysis. The sample over-represented Texans and specific demographic classes, such as female and bachelor's degree holders, and under-represented others, such as men who did not complete high school and males 18 to 21 years old. Therefore, the survey sample proportions in 120 categories[15] (two gender-based, five age-based, six educational-attainment groups, and "respondent is Texan or not?") were scaled using the 2013 American Community Survey's Public Use Microdata Sample (PUMS 2013). These scale factors were used as person-level weights to un-bias person-related summary statistics (e.g., binary opinion whether AVs are realistic or not) and model-based parameter estimates.

Similarly, some household groups were under- or over-represented. Thus, household weights were calculated for 130 categories[16] (4 household size groups, 4 household workers groups, 5 vehicle ownership groups, and "household is Texan or not?") using PUMS 2013 data. These household weights were used to un-bias household-related (e.g., WTP for new technologies and vehicle transaction decisions) model estimates and summary statistics.

[15] Out of 120 categories, 4 were missing in the sample, and were merged with adjacent categories.

[16] There are 160 combinations of traits (4 x 4 x 5 x 2 = 160), but there are only 130 categories because some of the categories cannot exist. For example, the number of workers cannot exceed household size. Out of 130 categories, 12 were missing in the sample, and were merged with adjacent categories.

8.3 GEOCODING

To understand the spread of survey respondents across U.S. and to account for the impact of built-environment factors (e.g., population density and population below poverty line) on household vehicle transaction and technology adoption decisions, the respondents' home addresses were geocoded using Google Maps API and spatially joined with U.S. census-tract-level shape file using open-source Quantum GIS. 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. Figure 8.1 shows the geocoded respondents, with most respondents living in the southern and eastern U.S.

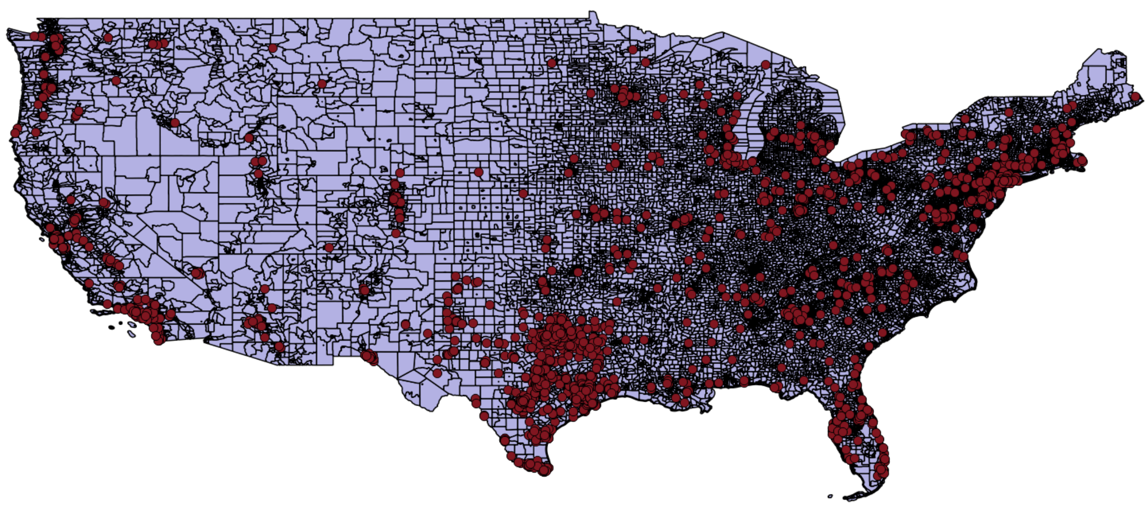

Figure 8.1: Geocoded Respondents across Continental USA

Chapter 9: Summary Statistics

9.1 Level 1 and Level 2 Technologies

Table 9.1 summarizes WTP for, interest in, and current adoption of Level 1 and Level 2 automation technologies[17]. The respondents showed the least interest in traffic sign recognition and left-turn assist technologies. Traffic sign recognition is of no interest to 52.6% of the respondents, and 54.4% noted they are unwilling to pay anything to add this technology to their vehicles. Left-turn assist is slightly more acceptable: 46.9% of the respondents are not interested in it, and 46.1% would not to pay anything for it. Blind-spot monitoring and emergency automatic braking appear to be the two most appealing technologies for Americans. Around half (50.7%) of the respondents are very interested in blind-spot monitoring, only 17.3% are not interested in it, and the smallest proportion of the respondents (only 23.7%) indicate $0 WTP for it. Emergency automatic braking is the second most interesting technology for Americans, with 45.8% of the very-interested respondents, only 22.8% of the not-interested respondents, and only 28.7% of the respondents with $0 WTP.

Not surprisingly, among these Level 1 and Level 2 automation technologies, electronic stability control (ESC) is the one most expected to be already present in the respondents' vehicles: 21.6% of those who have a vehicle reported having this technology in at least one household vehicle, and it is possible that many respondents are unaware that their vehicles now come equipped with such technology (since ESC has been mandated on all new passenger vehicles in the US since 2012 model year [NHTSA 2012]). The second most adopted technology is adaptive cruise control (ACC), with 12.8% of the respondents (who have at least one vehicle) having already adopted this

[17] Level 1 and Level 2 automations are considered together and used interchangeably at a few places, since a combination of Level 1 technologies leads to Level 2 automation.

technology. The least adopted technology is traffic sign recognition, as it is present in only 2.1% of the respondents' vehicles, while pedestrian detection has a slightly higher rate of adoption, at 3.3%.

The respondents' WTP for Level 1 and Level 2 technology varies significantly[18]. The average WTP (among the respondents who are willing to pay some positive amount for the technology) to add ESC to an existing or a future vehicle exceeded the projected price after five years: $79 (see Table 9.3[19]) versus $70. For every other technology, the average WTP (of the respondents who are ready to pay for the technology) is lower than the estimated future price after five years. For example, average WTP to add emergency automatic braking is $257 (versus $320, the projected price after five years) and for blind-spot monitoring, it is $210 (versus $280). The worst ratio of the average WTP to the projected price is for the adaptive headlights: $345 versus $700. Respondents value this technology significantly; in fact, it is the second most valued technology in terms of average WTP (of the respondents who are ready to pay for the technology), but respondents probably believe that the projected price is still too high.

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[18] Before asking a WTP question, respondents were provided with a price forecast for a particular technology. For example, the price forecast for ESC was "Current Price: $100; Price after 5 years: $70; Price after 10 years: $50". It is difficult to estimate the price of a particular Level 1 or Level 2 technology, since these technologies are provided in packages. For example, BMW provides a $1900 package with lane departure warning, forward collision braking, adaptive cruise control, pedestrian detection, and blind-spot monitoring. Thus, after analyzing different packages, current prices for each of these technologies were determined. Subsequently, 30% price reduction in the next 5 years and a 50% price reduction in the next 10 years were considered (with 7% annual price reduction rate) to provide future price estimates of these technologies.

[19] Table 9.3 demonstrates average WTP for CAV technologies. The second column represents average WTP of all respondents, and the third column summarizes the WTP of those who indicated WTP more than $0 for a specific technology.

Table 9.1: Population-weighted Summaries for Level 1 and Level 2 Technologies (N_{obs}=2,167)

Response Variables	**Percentages**	**Response Variables**	**Percentages**
Electronic Stability Control			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	33.4%	Yes	21.6%
Less than $60	16.8%	*Interested in Technology*	
$60 to $79	20.4%	Not interested	29.1%
$80 to $119	21.6%	Slightly interested	41.6%
$120 and more	7.8%	Very interested	29.3%
Lane Centering			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	41.7%	Yes	3.9%
Less than $200	21.4%	*Interested in Technology*	
$200 to $399	14.2%	Not interested	37.8%
$400 to $599	12.4%	Slightly interested	39.0%
$600 and more	10.3%	Very interested	23.2%
Left Turn Assist			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	46.1%	Yes	3.8%
Less than $100	14.9%	*Interested in Technology*	
$100 to $299	23.6%	Not interested	46.9%
$300 to $399	8.1%	Slightly interested	35.3%
$400 and more	7.3%	Very interested	17.8%
Cross Traffic Sensor			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	32.8%	Yes	9.6%
Less than $100	15.2%	*Interested in Technology*	
$100 to $199	14.4%	Not interested	31.7%
$200 to $399	24.6%	Slightly interested	38.9%
$400 and more	13.0%	Very interested	29.3%
Adaptive Headlights			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	41.1%	Yes	9.5%
Less than $150	17.7%	*Interested in Technology*	
$150 to $349	17.4%	Not interested	34.7%
$350 to $649	15.2%	Slightly interested	39.6%
$650 and more	8.7%	Very interested	25.6%

Table 9.1 (continued)

Pedestrian Detection			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	37.5%	Yes	3.3%
Less than $100	16.0%	*Interested in Technology*	
$100 to $199	12.8%	Not interested	31.4%
$200 to $399	24.2%	Slightly interested	37.1%
$400 and more	9.5%	Very interested	31.5%
Adaptive Cruise Control			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	37.7%	Yes	12.8%
Less than $150	26.2%	*Interested in Technology*	
$150 to $249	14.8%	Not interested	32.1%
$250 to $349	11.9%	Slightly interested	37.1%
$350 and more	9.4%	Very interested	30.8%
Blind-spot Monitoring			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	23.7%	Yes	9.9%
Less than $150	29.5%	*Interested in Technology*	
$150 to $249	18.2%	Not interested	17.3%
$250 to $349	14.7%	Slightly interested	31.9%
$350 and more	13.9%	Very interested	50.7%
Traffic Sign Recognition			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	54.4%	Yes	2.1%
Less than $100	15.0%	*Interested in Technology*	
$100 to $199	9.6%	Not interested	52.6%
$200 to $299	10.1%	Slightly interested	30.1%
$300 and more	10.9%	Very interested	17.3%
Emergency Automatic Braking			
Willingness to Pay to Add		*Present in a Vehicle**	
Do not want to pay anything	28.7%	Yes	5.4%
Less than $200	26.8%	*Interested in Technology*	
$200 to $299	18.3%	Not interested	22.8%
$300 to $399	13.7%	Slightly interested	31.5%
$400 and more	12.4%	Very interested	45.8%
*Among the respondents who reported to have at least one vehicle in their households.			

9.2 Connectivity and Advanced Automation Technologies

Table 9.2 summarizes respondents' WTP to add connectivity, self-parking valet system, and Level 3 and Level 4 automation. It is evident that more than half of the respondents are not ready to pay for any of the advanced automation technology, but comparatively fewer (only around 39%) indicated $0 WTP to add connectivity.

Table 9.2: Population-weighted WTP for Adding Connectivity and Advanced Automation Technologies (N_{obs}=2,167)

Response Variables	Percentages	Response Variables	Percentages
WTP for Adding LV3 Automation		**WTP for Adding LV3 Valet Tech**	
Do not want to pay anything	55.4%	Do not want to pay anything	51.7%
Less than $2,000	13.3%	Less than $250	13.6%
$2,000 to $5,999	13.9%	$250 to $1,249	20.1%
$6,000 to $9,999	9.4%	$1,250 to $1,749	8.1%
$10,000 and more	7.9%	$1,750 and more	6.5%
WTP for Adding LV4 Automation		**WTP for Adding Connectivity**	
Do not want to pay anything	58.7%	Do not want to pay anything	39.1%
Less than $6,000	14.4%	Less than $75	20.3%
$6,000 to $13,999	10.3%	$75 to $124	16.5%
$14,000 to $25,999	9.3%	$125 to $174	11.6%
$26,000 and more	7.3%	$175 and more	12.5%

Table 9.3: Population-weighted Average WTP for AV Technologies (N_{obs}=2,167)

Average WTP for Adding Technology	For all Respondents	For those with WTP > 0
Electronic Stability Control	$52	$79
Lane Centering	$205	$352
Left Turn Assist	$119	$221
Cross Traffic Sensor	$169	$252
Adaptive Headlights	$203	$345
Pedestrian Detection	$145	$232
Adaptive Cruise Control	$126	$202
Blind-spot Monitoring	$160	$210
Traffic Sign Recognition	$93	$204
Emergency Automatic Braking	$183	$257
Connectivity	$67	$111
Self-parking Valet	$436	$902
Level 3 Automation	$2,438	$5,470
Level 4 Automation	$5,857	$14,196

Among those who are willing to pay for advanced automation, the average WTP for Level 3 automation is $5,470 and for Level 4 automation, it is $14,196 (see Table 2.3). Self-parking valet technology is valued at around $902 (with a simulation-projected price of $1,400 after 5 years, which may be too low [given how complex discerning a proper/legal parking spot can be in many settings]) and connectivity is valued at only $111 (projected price after five years is $140).

9.3 OPINIONS ABOUT CAV TECHNOLOGIES AND RELATED ASPECTS

Table 9.4 summarizes the respondents' opinions about their own behavior, automation technologies, and related aspects. Most Americans perceive themselves as good drivers (88.2%), enjoy driving a car (75.7%), and tend to wait before adopting new technologies (79.3%). Respondents are indecisive on the topic of whether AVs will drive better than them (around one-third agrees, around one-third disagrees, and the last third has no opinion on this).

Table 9.4: Individual-weighted Opinions of Respondents (N_{obs}=2,167)

Opinions	Agree	Neutral	Disagree
I believe that I am a very good driver myself.	88.2%	9.3%	2.6%
I think AVs will drive more safely than my driving.	33.4%	31.6%	35.0%
Driving a car is something I enjoy.	75.7%	15.4%	8.9%
I generally tend to wait for a new technology if it proves itself.	79.3%	14.2%	6.5%
AVs are a useful advance in transportation.	54.4%	26.0%	19.7%
The idea of AVs is not realistic.	43.5%	26.8%	29.7%
AVs will be a regular mode of transport in 15 years.	41.4%	32.2%	26.4%
AVs scare me.	58.4%	19.4%	22.2%
I have waited a long time for AVs.	23.2%	23.8%	53.1%
I do not think that AVs will function reliably.	49.1%	29.8%	21.2%
I would be comfortable in sending my AVs out knowing that I am liable for an accident.	19.5%	19.9%	60.5%

Around 54.4% of the respondents perceive AVs as a useful advancement in transportation, but 58.4% are scared of them. Only around one-quarter (23.2%) of the

respondents have been waiting for AV availability and only 19.5% will be comfortable sending an AV driving on its own, assuming that they as owners are liable for any accident it might cause. 41.4% of the respondents agree with the statement that AVs will be omnipresent in the future. Around 49% of the respondents think that AVs will function reliably, while 44% believe the idea of AVs is not realistic.

Table 9.5: Individual-weighted Opinions about Connectivity and AVs' Production (N_{obs}=2,167)

Comfortable in allowing a vehicle to transmit information to…	**Comfortable**	**Neutral**	**Uncomfortable**
Surrounding vehicles	50.4%	19.8%	29.8%
Vehicle manufacturers	42.9%	26.5%	30.6%
Insurance companies	37.0%	26.5%	36.4%
Transportation planners	40.9%	29.2%	30.0%
Toll operators	35.9%	30.9%	33.3%
To develop Level 4 AVs, I would trust:	**Percentage**		
Technology companies (e.g., Google, Apple, Microsoft, and Samsung)	62.3%		
Mass-market vehicle manufacturers (e.g., Toyota and Ford)	45.5%		
Luxury vehicle manufacturers (e.g., BMW and Mercedes)	49.5%		
Government agencies (e.g., NASA and DARPA)	1.4%		
Universities and research institutions	0.3%		
I would not trust any company to develop a Level 4 AVs.	7.9%		
Unsure	1.2%		

Table 9.5 summarizes the respondents' opinions about their comfort in allowing their CVs to share information with certain organizations or other vehicles, as well as whom they trust to develop AVs. It is interesting to note that more than half of the respondents (50.4%) are comfortable if their vehicle transmits information to other vehicles, and 42.9% are comfortable sending information to the vehicle manufacturer. Respondents were most uncomfortable sending information to insurance companies (36.4%) and toll operators (33.3%).

Most respondents are willing to trust technology companies (62.3%) and luxury vehicle manufacturers (49.5%) for production of well-designed AVs. Mass-market manufacturers come in third place, with support from 45.5% of the (population-weighted) respondents, and around 7.9% of the respondents do not trust any company to manufacture AVs.

9.4 Opinions about AV Usage by Trip Types and Long-distance Travel

Table 9.6 demonstrates the respondents' opinions about AV use for different trip types and long-distance travel. Interestingly, around the same share of (population-corrected) respondents reported unwillingness to use AVs for short-distance (42.5%) or long-distance (40.0%) trips (under and over 50 miles, respectively). Around 40% reported a willingness to use AVs for their everyday trips, but just one-third plan to use them for their or their children's school trips. In the context of long-distance travel, the highest share of respondents (37.2%) plan to use AVs for trips with one-way distances between 100 and 500 miles. People also believe the number of long-distance trips they make will increase, by an average of 1.3 per month, after they have acquired an AV.

Table 9.6: Individual-weighted Summaries for AV Usage by Trip Type (N_{obs}=2,167)

I will use AVs during a…	**Percentage**	**I will use AVs for trips…**	**Percentage**
Work trip	41.1%	Between 50 and 100 miles	33.6%
School trip	33.3%	Between 100 and 500 miles	37.2%
Shopping trip	42.1%	Over 500 miles.	28.0%
Personal business trip	39.7%	I will not use AVs for such trips.	40.0%
Social or recreational trip	44.6%	**Average increase in the number of long-distance trips**	
I will not use AVs.	42.5%	Additional number of long-distance trips (per month)	1.3

Chapter 10: Forecasting Long-Term Adoption of CAV Technologies

10.1 Simulation-based Framework

The simulation-based framework that forecasts the long-term adoption of CAV technologies consists of several stages, pursued together at a one-year time step. The first stage is a vehicle transaction and technology adoption model (as shown in Figure 10.1) that simulates the households' annual decisions to sell a vehicle ("sell"), buy vehicles ("buy"), sell a vehicle and buy vehicles ("replace"), add technology to the existing vehicles ("add technology"), and take no action ("do nothing"). A multinomial logit (MNL) model was estimated in BIOGEME (Bierlaire 2003) to determine the probabilities of making these decisions and use these probabilities in the Monte Carlo method to ascertain the vehicle transaction and technology adoption choice of each household after each year. Initial model specifications included all explanatory variables and the MNL model was re-estimated using stepwise elimination by removing the covariate with the lowest statistical significance. Although most of the explanatory variables enjoy a p-value greater than .05 (|z-stat| > 1.96), covariates with p-values lower than 0.32 (which corresponds to a |z-stat| of greater than 1.0) were also kept in the final specification. McFadden's R-Square[20] and adjusted R-square are calculated to measure the models' goodness of fit.

In the case of a "sell" decision[21], the oldest vehicle (within a selling household) is disposed of. In the case of a "buy" decision, it is assumed that a household will buy (or lease) one or two vehicles, and that each vehicle can be acquired new or used. It is

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[20] McFadden's R-Square = $1-\frac{log(L_{full})}{log(L_{null})}$ and McFadden's adjusted R-Square = $1-\frac{\left(log(L_{full})\right)-n}{log(L_{null})}$, 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.

[21] It was assumed that the household sells or disposes only one vehicle at a time.

important to determine whether a household purchases a new or used vehicle, since it was assumed that Level 3 and Level 4 automation cannot be retrofitted into used vehicles and that the cost of retrofitting existing vehicles with self-parking valet systems, Level 1 automation, and Level 2 automation are four times the cost of adding these technologies into a new vehicle (while it is being manufactured, essentially). Using the survey data, binary logit models were estimated in BIOGEME to determine these probabilities: 1) whether a household acquiring a vehicle will purchase one or two vehicles and 2) whether each vehicle will be new or used. These probabilities were used in a Monte Carlo simulation (so that choices for each household in each year have random component, to reflect the uncertain nature of choice forecasting). Subsequently, DSRC-type connectivity is added to the purchased vehicle if a household's WTP for connectivity exceeds its price. If the purchased vehicle is used, then Level 1 and Level 2 automation are added based on the household's total budget for Level 2 technologies, and preferences and WTP for each Level 2 technology (or Level 1 technology, if only one technology is added to the vehicle). As mentioned earlier, respondents were also separately asked about WTP for a self-parking valet system[22], so this option is added to the used vehicle if the household's WTP exceeds that technology's price. If the purchased vehicle is new and the household's WTP for Level 4 automation exceeds the price of its addition, then Level 4 is added to the new vehicle. Otherwise a similar rule is checked for Level 3 automation. If the condition is met for Level 3, this automation is added to the new vehicle; otherwise, a self-parking valet system and Level 1 or Level 2 automation is added to the new vehicle with the same rules as described for the used-vehicle case.

[22] A self-parking valet system was not characterized as a specific level of automation, but was assumed to be present in any vehicle having Level 3 or Level 4 automation.

In the case of a “replace” decision, a household is assumed to first choose a “sell” option, followed by a “buy” decision. In the case of an “add technology” decision, if an existing vehicle already has Level 3 or Level 4 automation, then no new technology is added to the vehicle. If this is not the case, then the existing technologies in the vehicle are excluded from the choice set, and a self-parking valet system (if not present in the existing vehicle) and Level 1 or Level 2 automation is added to the existing vehicle with the same rules as described for the used-vehicle case. In the “do nothing” case, all vehicles are retained and no technology is added. If a household does not own a vehicle, but the simulation suggests it choose “sell”, “replace”, or “add technology” options, the household is forced to pick the “do nothing” option. Finally, the population-weighted adoption rates of all technologies are extracted by the simulation program, every year. Please see *Appendix A* to find MATLAB code performing this simulation.

This simulation framework does not consider changes in household demographics over time (other than the respondent’s age and his/her household’s overall vehicle ownership, since they are explanatory variables in the vehicle transaction and technology adoption model). Integrating household evolution models (as used in Musti and Kockelman [2011] and Paul et al. [2011]) may improve estimates of adoption rates and the nation’s fleet evolution.

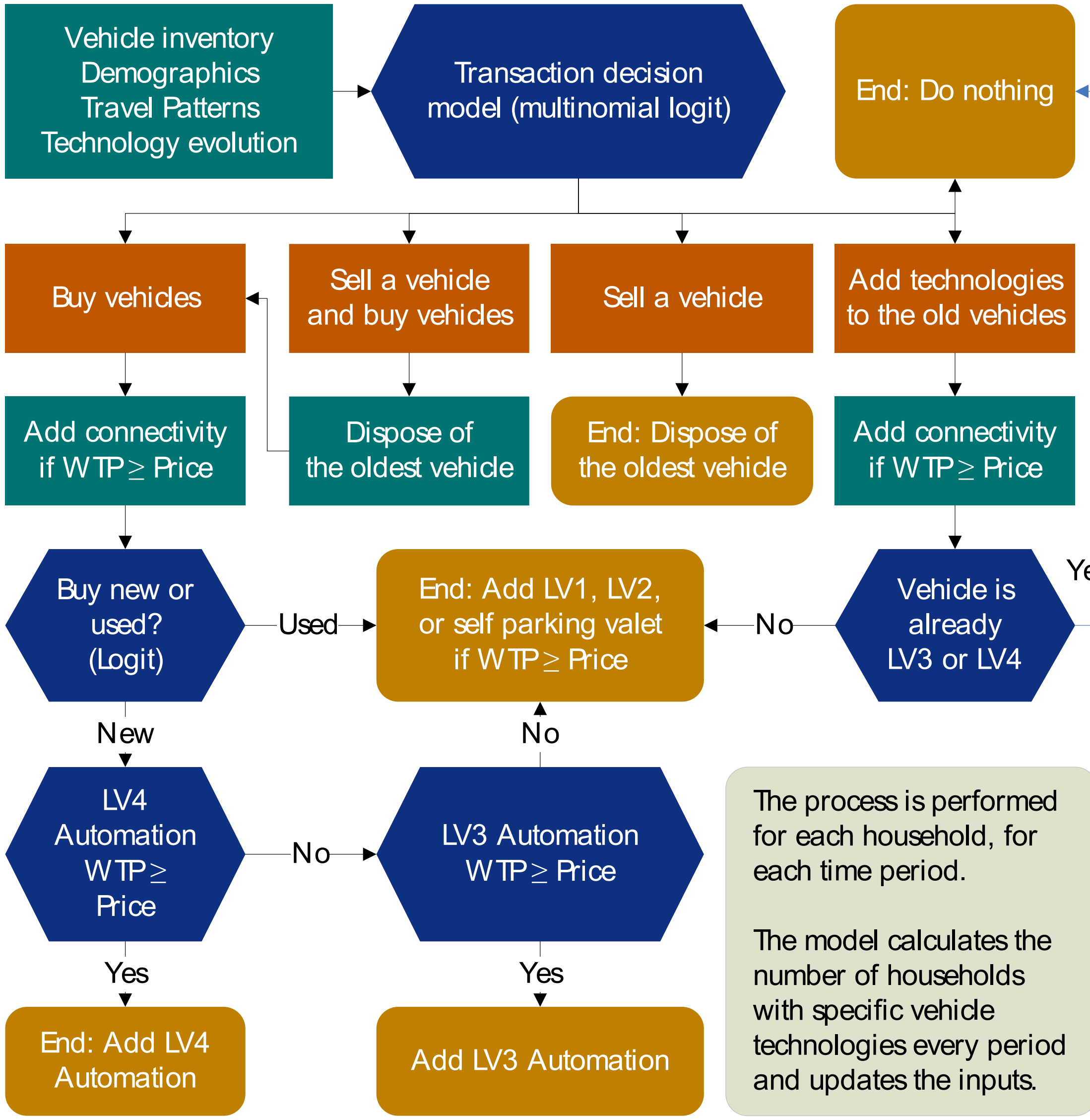

Figure 10.1: The Simulation-based Framework to Forecast Long-term Technology Adoption

10.2 Vehicle Transaction and Technology Adoption: Model Specifications

Table 10.1 summarizes key statistics for (population-weighted) person- and household-level variables, geocoded location variables, and transaction decision variables, as included in the vehicle transaction and technology adoption models.

Table 10.1: Population-weighted Summary Statistics (N_{obs}=2,167)

Explanatory Variables	**Mean**	**SD**	**Min.**	**Max.**
Person Variables				
Age (years)	44.980	16.623	21	70
Male?	0.4897	0.5000	0	1
Single?	0.3358	0.4724	0	1
Bachelor's degree holder?	0.2561	0.4366	0	1
Full-time worker?	0.3146	0.4645	0	1
Have U.S. driver's license?	0.9045	0.2940	0	1
Disabled?	0.1285	0.3348	0	1
Annual vehicle-miles traveled over 9,000 miles?	0.3971	0.4894	0	1
Retired?	0.1848	0.3882	0	1
Drive alone for work trips?	0.5151	0.4999	0	1
Household Variables				
More than 3 members in the household?	0.2553	0.4361	0	1
Number of workers in the household	1.1944	0.9220	0	7
More than 1 worker in the household?	0.3491	0.4768	0	1
Household income	64,640	51,924	5,000	250,000
Age of the oldest vehicle in the household (in years)	10.661	7.3239	0	30
Number of vehicles owned by the household	1.7828	1.0176	0	6
At least one vehicle owned by the household?	0.9292	0.2566	0	1
Number of vehicles sold in the past 10 years	0.4230	0.6651	0	5
At least one vehicle sold in the past 10 years?	0.3488	0.4767	0	1
Location Variables				
% of families below poverty line in the census tract	12.301	10.155	0	77
Employed and over 16 years of age (per square mile)	2,826.0	6,232.6	1.1917	1,13,187
Population density (per square mile)	3,958.8	8,680.4	1.6496	1,32,409
Distance to transit stop (from home) exceeds 3 miles?	0.4868	0.4999	0	1
Distance to downtown (from home) exceeds 5 miles?	0.6428	0.4793	0	1
Response Variables	**Mean**	**SD**	**Min.**	**Max.**
Transaction Decisions				
Sell (a household vehicle in the coming year)	0.0382	0.1916	0	1
Replace a vehicle	0.2406	0.4276	0	1
Buy vehicles	0.1639	0.3703	0	1
Add technology to existing vehicles	0.0890	0.2848	0	1
Do nothing (maintain one's current vehicle holdings)	0.4683	0.4991	0	1
Buy Two Vehicles (in the coming year)?	0.0766	0.2659	0	1
Buy a New Vehicle (in the coming year)?	0.6495	0.4771	0	1

Table 10.2 shows the transaction model's final specification. The alternative specific constants (ASCs) indicate that, everything else being equal, households have inherent inclination and disinclination for "buy" and "replace" options, respectively. Specifically, older and single individuals with more than one worker in the household, who live farther from downtown in a lower-income neighborhood (all other attributes constant), are less likely to sell their vehicles in the coming year, while males in households with more vehicles appear more inclined to sell. Bachelor's degree holders, full-time workers, and younger, male respondents who drive alone for work, have more vehicles, and live in households with more than one worker are estimated to be more likely to replace a vehicle than others. Older and single (unmarried) respondents whose households own more vehicles appear to be less likely to buy a vehicle in the coming year. In contrast, respondents who drive alone to work, reside in households with more than one worker and more than three members, and have older vehicles appear more likely to buy a vehicle in the coming year. It is interesting to note that bachelor's degree holders who drive alone for work trips and live in neighborhoods with a higher density of employed individuals are more inclined toward the "add technology" option than "do nothing". However, all else equal, older individuals who have older vehicles are more likely to prefer the "do nothing" option over the "add technology" option.

Table 10.2: Transaction Decisions (Weighted Multinomial Logit Model Results)

Covariates	Coef.	T-stat
ASC_{Sell}	0	-fixed-
$ASC_{Replace}$	-1.810	-4.33
ASC_{Buy}	0.572	1.84
$ASC_{Add\ Technology}$	0	-fixed-
Sell		
Age (years)	-0.067	-10.15
Distance of downtown (from home) exceeds 5 miles?	-0.502	-2.06
Male?	0.686	2.64
Number of vehicles owned by the household	0.626	5.37
% of families below poverty line in the census tract	-0.020	-1.57
Single?	-0.884	-3.06
More than 1 worker in the household?	-0.833	-3.03
Replace		
Age (years)	-0.027	-6.29
Bachelor's degree holder?	0.556	4.93
Drive alone for work trips?	0.415	3.18
Full-time worker?	0.175	1.38
Male?	0.154	1.40
Number of vehicles owned by the household	0.127	1.84
At least one vehicle owned by the household?	1.440	3.65
Retired?	0.477	2.46
More than 1 worker in the household?	0.310	2.47
Buy		
Age (in years)	-0.039	-7.29
Drive alone for work trips?	0.172	1.30
More than 3 members in the household?	0.498	3.73
Age of the oldest vehicle in the household (in years)	0.016	1.73
Number of vehicles owned by the household	-0.283	-3.26
% of families below poverty line in the census tract	0.015	2.92
Retired?	0.265	1.22
Single?	-0.146	-1.03
More than 1 worker in the household?	0.171	1.25
Add technology		
Age (in years)	-0.041	-10.52
Bachelor's degree holder?	0.382	2.34
Drive alone for work trips?	0.438	2.71
Age of the oldest vehicle in the household (in years)	-0.033	-2.88

Table 10.2 (continued)

Employed over 16 years (per square mile)	1.54E-05	2.11
Retired?	0.625	2.41
Fit statistics		
Null log-likelihood	-3487.65	
Final log-likelihood	-2688.66	
McFadden's R-square	0.229	
Adjusted R-square	0.220	
Number of observations	2,167	

Note: The "do nothing" option is base here.

Table 10.3 shows the "bought two vehicles?" model's final specification. Male and disabled respondents whose households sold more vehicles in the past 10 years, have more workers, and live farther from transit stop in highly populous neighborhoods (with everything else held constant) are more likely to purchase two vehicles. However, single respondents who travel more and live in poorer neighborhoods are inclined to buy only one vehicle.

Table 10.3: Bought Two Vehicles? (Binary Logit Model Results)

Covariates	**Coef.**	**T-stat**
Constant	-3.019	-6.74
Number of vehicles sold in the past 10 years	0.412	2.07
Distance to transit stop (from home) exceeds 3 miles?	0.527	1.67
Distance to downtown (from home) exceeds 5 miles?	-0.324	-1.01
Annual vehicle-miles traveled over 9,000 miles?	-0.552	-1.88
Disable?	0.670	1.68
Number of workers in the household	0.335	1.87
Male?	0.460	1.63
Population density (per square mile)	2.62E-05	3.91
% of families below poverty line in the census tract	-0.021	-1.54
Single?	-0.744	-2.15
Fit statistics		
Null log-likelihood	-279.24	
Final log-likelihood	-257.68	
McFadden's R-square	0.077	
Adjusted R-square	0.074	
Number of observations	1033	

Table 10.4 shows the “bought new vehicle?” model’s final specification. Older, licensed drivers, full-time workers, and male respondents whose households own more vehicles, have higher income, and live in neighborhoods with a higher density of employed individuals (all other attributes held constant) are more inclined towards buying new vehicles. In contrast, disable respondents who have more workers in the household, sold at least one vehicle in the past 10 years, and live in the highly populous neighborhoods are more likely to buy used vehicles.

Table 10.4: Bought New Vehicle? (Binary Logit Model Results)

Covariates	**Coef.**	**T-stat**
Constant	-2.584	-3.53
Number of vehicles owned by the household	0.418	2.17
At least one vehicle owned by the household?	2.304	4.32
Age of the oldest vehicle in the household (in years)	-0.093	-4.39
Number of vehicles sold in the past 10 years	0.535	2.01
At least one vehicle sold in the past 10 years?	-2.162	-5.12
Disabled?	-0.639	-1.51
Number of workers in the household	-0.462	-2.98
Age (years)	0.011	1.41
Male?	0.349	1.44
Have U.S. driver’s license?	0.774	1.25
Household income	1.45E-05	4.25
Full-time worker?	0.708	2.73
Population density (per square mile)	-3.41E-05	-1.35
Employed and over 16 years of age (per square mile)	4.41E-05	1.29
Fit statistics		
Null log-likelihood	-467.04	
Final log-likelihood	-340.71	
McFadden’s R-square	0.270	
Adjusted R-square	0.262	
Number of observations	721	

The respondent’s age, number of vehicles owned by the household, number of vehicles sold in the past 10 years, indicator for owning at least one vehicle, indicator for selling at least one vehicle in the past 10 years, and age of the oldest vehicle in the household are annually updated in the simulation.

10.3 Forecasted Adoption Rates of CAV Technologies

10.3.1 Scenarios Description

This simulation forecasts the annual adoption rates[23] of CAV technologies over the next 30 years (2016 to 2045) under eight different scenarios based on WTP, technology pricing, and regulation scenarios (see Table 10.5).

As indicated in Tables 9.1 and 9.2, many respondents do not want to pay anything to add CAV technologies. For example, more than 50% of respondents have $0 WTP to add Level 3 and Level 4 automation. Perhaps, these respondents are not able to conceive a world with only CAVs and also may have various safety and reliability concerns about the technology. As the public learns more about CAVs and more people gain familiarity with these technologies, these perceptions, and potential behavioral responses are apt to change, in some cases rapidly. In Scenario 1, the original WTP (as reported by the respondents) was considered, and assumed constant over time. However, for all other scenarios (2 to 8), respondents who reported $0 WTP, were assigned a non-zero WTP[24] for year 2015, and WTP's temporal variation followed as per annual increment rates.

Scenarios 1 and 2 do not consider any NHTSA's current and probable technology adoption regulations, but the remaining scenarios (3 to 8) assume mandatory adoption of ESC from year 2015[25] and connectivity from year 2020[26] on all new vehicles.

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[23] Technology adoption rate refers to the percentage of the vehicles (population-weighted) having a specific technology. Vehicles with Level 3 and Level 4 automation are assumed to have all Level 2 automation technologies.

[24] To assign WTP to the respondents who do not want to pay anything for specific technology, sample was classified into 40 categories (based on household size, number of workers, and household vehicle ownership) and subsequently, a household who does not want to pay anything for specific technology, was assigned a WTP of 10th percentile of all non-zeros WTP values in the household's category.

[25] ESC has been mandated on all new passenger vehicles in the US since 2012 model year (NHTSA 2012).

Table 10.5: WTP Rise, Technology Price Reduction, and Regulation Scenarios

Scenario	Annual Increase in WTP	Annual Technology Price Reduction Rate	Regulations
1	0%	10%	No
2	0%, but no zero WTP	10%	No
3	0%, but no zero WTP	5%	Yes
4	0%, but no zero WTP	10%	Yes
5	5%	5%	Yes
6	5%	10%	Yes
7	10%	5%	Yes
8	10%	10%	Yes

Note: In the "no zero WTP" scenarios, the tenth percentile WTP (among non-zero WTP individuals) for the individual's household-demographic cohort was used.

Table 10.6: Technology Prices at 5% Annual Price Reduction Rates

Technology	2015	2020	2025	2030	2035	2040	2045
Electronic Stability Control	$100	$77.4	$59.9	$46.3	$35.8	$27.7	$21.5
Lane Centering	$950	$735.1	$568.8	$440.1	$340.6	$263.5	$203.9
Left-turn assist	$450	$348.2	$269.4	$208.5	$161.3	$124.8	$96.6
Cross Traffic Sensor	$550	$425.6	$329.3	$254.8	$197.2	$152.6	$118.1
Adaptive Headlights	$1,000	$773.8	$598.7	$463.3	$358.5	$277.4	$214.6
Pedestrian Detection	$450	$348.2	$269.4	$208.5	$161.3	$124.8	$96.6
Adaptive Cruise Control	$400	$309.5	$239.5	$185.3	$143.4	$111.0	$85.9
Blind-spot Monitoring	$400	$309.5	$239.5	$185.3	$143.4	$111.0	$85.9
Traffic Sign Recognition	$450	$348.2	$269.4	$208.5	$161.3	$124.8	$96.6
Emergency Automatic Braking	$450	$348.2	$269.4	$208.5	$161.3	$124.8	$96.6
Connectivity	$200	$154.8	$119.7	$92.7	$71.7	$55.5	$42.9
Self-parking Valet	$2,000	$1,548	$1,198	$926.6	$717.0	$554.8	$429.3
Level 3 Automation	$15,000	$11,607	$8,981	$6,949	$5,377	$4,161	$3,220
Level 4 Automation	$40,000	$30,951	$23,950	$18,532	$14,339	$11,096	$8,586

As mentioned earlier, it is difficult to estimate the price of a particular Level 1 or Level 2 technology, since automobile companies provide these technologies in packages. Thus, current prices for these technologies were estimated by analyzing packages provided by BMW, Mercedes, and other manufacturers. Prices to add connectivity, Level 3, and Level 4 automation were estimated based on experts' opinions. Table 10.6 shows

[26] NHTSA is expected to require connectivity on all vehicles produced after year 2020 (Automotive Digest 2014).

an example of temporal variation of the prices to add CAV technologies to the new vehicles[27] for the annual price reduction rate of 5%.

10.3.2 Comparison of Technology Adoption in Eight Scenarios

Tables 10.7 to 10.10 present the adoption rates for every 5 years across all eight scenarios. Substantial differences are visible between the long-term adoption rates of all technologies (except Level 3 and Level 4 automation)[28] in Scenarios 1 (constant WTP) and 2 (constant WTP, and all zero-WTP households replaced with low WTP value). For example, in 2045, the DSRC connectivity's adoption rate is estimated to be 59.5% in Scenario 1 and 83.5% in Scenario 2. Such differences emerge because many households cannot adopt some technologies in Scenario 1, even prices fall low, due to their initial, stated (and assumed-constant) zero WTP.

The regulations' (regarding adoption of ESC and connectivity) effects on CAV technologies' adoption rates can be observed by comparing the results of Scenario 2 (see Table 10.7) and Scenario 4 (see Table 10.8), since WTP and technology prices have the same dynamics in both scenarios. In Scenario 2 (with no technology adoption regulations in place), ESC and connectivity options have adoption rates of 43.8% and 35.2% by 2025, and these numbers jump to 98.4% and 88.4% under Scenario 4, thanks to regulations.

The technology pricing impacts on the adoption of CAV technologies can be visualized by comparing adoption rates in Scenarios 3 and 4 (or 5 and 6, or 7 and 8),

[27] In this study, costs for retrofitting a self-parking valet system, Level 1, and Level 2 automations into the used vehicles are assumed to be four times the cost of adding these technologies to new vehicles. For example, as per Table 10.6, the cost to add traffic sign recognition to the new vehicle is $450, but the cost for retrofitting it into a used vehicle is assumed to be $1800.

[28] In Scenario 2, all respondents with $0 WTP are assigned non-zero WTP values, but new WTP values are not enough to make advanced automation technologies affordable, even at 10% price drop rates. Thus, Level 3 and Level 4 automations' adoption rates differ very little between Scenarios 1 and 2.

since these scenarios include regulations and have same temporal variations in WTP, but different technology price variations. Table 10.8 shows that most of the technologies' long-term adoption rates under annual 10% technology price reduction (Scenario 4) are much higher[29] than those under a 5% price-reduction (Scenario 3), since technologies are obviously affordable for many more households in Scenario 4 as compared to Scenario 3. For example, in 2045, Level 4 automation's adoption rates are 24.8% in Scenario 3 and 43.4% in Scenario 4.

The effect of WTP increments on CAV technologies' adoption rates can be observed by comparing the results of Scenarios 4, 6, and 8 (or 3, 5, and 7), since these scenarios incorporate NHTSA regulations, and same temporal variations of technology pricing, but different WTP variations. As expected, Tables 10.8, 10.9, and 10.10 demonstrate that, for most of the technologies, the long-term adoption rates in 0%, 5%, and 10% WTP increment scenarios show corresponding increases. For example, in 2045, Level 4 automation's adoption rates in Scenarios 4, 6, and 8 are 43.4%, 70.7%, and 87.2%, respectively.

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[29] However, for a few technologies, adoption rates are lower in Scenario 4 as compared to Scenario 3 at some point in time. For example, ESC's adoption rates (in 2025) are 98.6% in Scenario 3 and 98.4% in scenario 4. These minor unintuitive differences might have occurred due to the noise of the simulation involving random number generation.

Table 10.7: Percentage of Vehicles with Technologies in Scenarios 1 and 2

Technology	**Scenario 1:** *Constant WTP, 10% drop in tech-prices, and no regulation*							**Scenario 2:** *No-zero-WTP, 10% tech-price drop, and no regulation*						
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Electronic Stability Control	24.3	25.3	33.2	43.3	52.7	58.2	63.8	24.3	32.3	43.8	61.2	76.7	83.2	92.9
Lane Centering	4.4	8.3	18.9	31.0	40.8	48.8	56.8	4.4	8.6	20.2	33.5	45.9	55.2	68.8
Left-turn assist	3.8	9.9	20.1	32.4	41.8	50.3	58.1	3.8	10.4	21.8	35.1	47.2	65.6	80.2
Cross Traffic Sensor	10.9	12.9	22.6	35.1	45.1	52.6	60.3	10.9	13.8	25.9	41.1	53.7	66.0	82.8
Adaptive Headlights	10.2	9.7	18.8	30.9	41.0	49.2	58.0	10.2	9.8	19.8	32.4	46.2	55.9	77.5
Pedestrian Detection	3.7	10.6	21.7	34.5	44.1	52.6	59.8	3.7	11.2	24.1	38.2	50.3	69.1	82.8
Adaptive Cruise Control	13.3	14.9	24.1	35.2	44.7	52.2	59.8	13.3	16.2	27.0	40.1	53.4	62.2	76.1
Blind-spot Monitoring	11.7	15.0	26.1	38.5	48.2	55.1	62.1	11.7	17.3	31.9	46.3	59.7	67.8	80.7
Traffic Sign Recognition	2.0	7.7	18.0	30.0	39.8	48.9	57.0	2.0	7.6	18.4	31.4	43.5	63.3	78.6
Emergency Automatic Braking	5.6	11.8	24.4	37.1	46.9	54.6	61.6	5.6	11.8	26.4	43.7	57.7	74.3	86.2
Connectivity	0	17.7	34.8	44.7	51.1	53.0	59.5	0	18.0	35.2	46.1	57.6	61.4	83.5
Self-parking Valet	0	9.1	21.4	33.9	45.1	52.5	61.2	0	9.2	21.6	34.5	46.3	54.4	73.5
Level 3 Automation	0	2.1	4.6	7.6	8.3	8.0	10.4	0	3.0	5.3	7.7	8.7	7.9	13.7
Level 4 Automation	0	3.9	11.1	19.7	28.6	37.0	43.0	0	3.0	10.2	19.0	28.7	37.9	43.8

Table 10.8: Percentage of Vehicles with Technologies in Scenarios 3 and 4

Technology	**Scenario 3:** *No-zero-WTP, 5% drop in tech-prices, and regulations*							**Scenario 4:** *No-zero-WTP, 10% drop in tech-prices, and regulations*						
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Electronic Stability Control	24.3	88.9	98.6	99.8	100	100	100	24.3	89.1	98.4	99.9	100	100	100
Lane Centering	4.4	6.1	12.0	19.7	27.1	33.1	40.7	4.4	8.5	19.9	33.0	45.5	53.9	66.5
Left-turn assist	3.8	7.9	14.2	21.3	28.1	35.1	42.5	3.8	10.0	21.8	35.0	46.5	60.6	75.1
Cross Traffic Sensor	10.9	11.7	16.8	22.9	31.9	39.1	47.4	10.9	13.7	25.4	39.8	52.2	62.2	76.8
Adaptive Headlights	10.2	7.6	11.2	18.3	26.4	32.6	39.9	10.2	9.5	19.6	32.3	46.1	53.6	71.6
Pedestrian Detection	3.7	8.3	15.0	23.2	30.7	38.3	45.5	3.7	10.7	24.0	37.5	49.7	63.4	77.1
Adaptive Cruise Control	13.3	13.2	18.4	25.7	33.2	39.2	46.5	13.3	16.5	28.1	39.7	53.0	60.4	73.4
Blind-spot Monitoring	11.7	13.8	20.3	29.7	39.6	45.7	53.5	11.7	16.5	31.6	45.6	59.1	66.0	77.2
Traffic Sign Recognition	2.0	5.4	10.5	17.7	24.9	31.4	38.1	2.0	7.3	18.2	30.9	42.7	58.7	73.9
Emergency Automatic Braking	5.6	8.6	15.6	26.1	34.7	43.4	51.2	5.6	12.3	26.3	42.3	57.2	69.1	80.9
Connectivity	0	36.5	88.2	98.4	99.7	100	100	0	41.3	88.4	98.4	99.7	100	100
Self-parking Valet	0	6.0	13.1	20.9	29.0	34.9	41.6	0	9.2	21.1	33.4	45.7	53.4	71.9
Level 3 Automation	0	1.9	3.2	4.5	6.5	8.1	8.9	0	2.7	5.1	7.5	8.7	8.2	13.9
Level 4 Automation	0	2.0	5.2	10.3	15.0	19.2	24.8	0	2.9	10.2	18.8	28.5	36.3	43.4

Table 10.9: Percentage of Vehicles with Technologies in Scenarios 5 and 6

Technology	**Scenario 5:** *5% rise in WTP, 5% drop in tech-price, and regulations*							**Scenario 6:** *5% rise in WTP, 10% drop in tech-price, and regulations*						
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Electronic Stability Control	24.3	89.1	98.3	99.9	100	100	100	24.3	88.7	98.2	99.9	100	100	100
Lane Centering	4.4	8.5	21.1	33.5	43.5	53.1	59.8	4.4	10.3	26.8	44.5	56.5	81.4	92.9
Left-turn assist	3.8	10.3	22.0	35.0	44.4	59.2	71.5	3.8	11.9	27.8	44.8	66.2	88.1	96.3
Cross Traffic Sensor	10.9	14.3	25.7	39.6	50.6	60.9	73.4	10.9	15.7	32.1	50.2	68.9	87.3	96.3
Adaptive Headlights	10.2	10.0	20.5	32.3	43.4	53.0	67.1	10.2	11.0	26.4	44.5	63.4	84.8	95.4
Pedestrian Detection	3.7	11.1	24.5	38.1	47.9	61.4	74.0	3.7	13.2	30.9	48.5	68.6	88.6	96.5
Adaptive Cruise Control	13.3	16.1	27.4	39.4	51.8	60.3	68.3	13.3	18.3	33.9	51.5	66.7	86.4	95.8
Blind-spot Monitoring	11.7	17.5	30.8	44.6	57.5	66.3	73.6	11.7	17.8	37.7	57.3	71.6	88.4	96.3
Traffic Sign Recognition	2.0	7.1	19.0	30.7	41.4	56.5	70.0	2.0	8.6	24.5	41.0	63.8	87.3	96.2
Emergency Automatic Braking	5.6	11.6	26.4	42.4	54.6	67.3	77.8	5.6	14.1	34.2	55.0	73.3	91.0	97.2
Connectivity	0	39.1	89.3	98.5	99.8	100	100	0	40.5	88.8	98.2	99.7	100	100
Self-parking Valet	0	8.6	21.8	34.0	44.4	52.4	67.1	0	10.2	26.9	44.2	64.5	85.6	96.5
Level 3 Automation	0	2.3	5.3	8.1	8.5	8.3	8.2	0	2.1	6.1	8.4	8.5	28.6	16.3
Level 4 Automation	0	3.3	10.8	19.0	27.2	35.9	43.2	0	4.7	15.1	27.2	38.3	45.7	70.7

Table 10.10: Percentage of Vehicles with Technologies in Scenarios 7 and 8

Technology	**Scenario 7:** *10% rise in WTP, 5% drop in tech-price, and regulations*							**Scenario 8:** *10% rise in WTP, 10% drop in tech-price, and regulations*						
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Electronic Stability Control	24.3	89.7	98.1	99.8	100	100	100	24.3	89.1	98.8	99.9	100	100	100
Lane Centering	4.4	10.8	25.5	42.1	55.1	78.1	90.3	4.4	13.5	32.8	51.2	79.0	94.0	97.9
Left-turn assist	3.8	11.6	26.5	43.0	65.1	83.6	95.0	3.8	14.1	34.1	60.9	87.3	96.4	98.4
Cross Traffic Sensor	10.9	15.6	30.8	48.3	65.4	84.6	95.0	10.9	18.2	39.3	63.6	87.0	96.6	98.5
Adaptive Headlights	10.2	11.4	25.0	42.3	58.5	81.3	92.5	10.2	13.4	32.8	55.8	81.4	95.5	98.2
Pedestrian Detection	3.7	12.9	28.8	45.8	67.9	84.6	95.3	3.7	15.3	37.6	63.7	87.9	96.8	98.7
Adaptive Cruise Control	13.3	18.0	31.7	49.1	62.5	82.8	92.8	13.3	20.3	40.4	60.2	83.2	95.4	98.2
Blind-spot Monitoring	11.7	18.5	35.6	54.6	67.7	85.4	94.0	11.7	20.5	45.5	66.4	85.9	96.3	98.6
Traffic Sign Recognition	2.0	9.0	23.2	39.0	62.0	82.6	94.9	2.0	10.9	30.0	57.9	86.4	96.4	98.4
Emergency Automatic Braking	5.6	13.9	32.9	52.1	72.4	88.0	96.4	5.6	16.6	41.5	68.4	90.0	97.3	98.9
Connectivity	0	41.8	89.1	98.3	99.7	100	100	0	41.3	89.4	99.0	99.9	100.0	100.0
Self-parking Valet	0	10.5	25.5	41.6	57.6	82.4	92.9	0	12.6	32.9	54.6	80.3	96.0	99.4
Level 3 Automation	0	2.5	5.9	8.3	8.2	26.5	25.5	0	3.5	6.0	7.7	27.7	11.6	2.9
Level 4 Automation	0	4.7	13.8	25.5	36.4	44.3	59.7	0	5.5	19.4	33.8	44.2	74.7	87.2

10.3.3 Adoption Rates of Connectivity and Level 2 Technologies

It is interesting to note that around 98% of the vehicle-fleet is likely to have ESC and connectivity in year 2025 and 2030, respectively, under NHTSA's current and probable regulations (Scenarios 3 to 8). However, it is worth noting that in case of no regulations, even at a 10% annual drop in technology prices and no-zero, but constant WTP (Scenario 2), 92.9% of vehicles would have ESC and 83.5% would have connectivity in 2045 (see Table 10.7). Thanks to NHTSA's regulations, which are likely to accelerate adoption of these technologies by 15 to 20 years, and make U.S. roads safer.

In Scenario 6 (5% rise in WTP and 10% drop in technology prices), Scenario 7 (10% rise in WTP and 5% drop in technology prices), and Scenario 8 (10% rise in WTP and 10% drop in technology prices), all Level 1 technologies are estimated to have more than 90% adoption rates in 2045. Level 1 technologies' adoption rates are further explored in Scenario 3 (5% drop in technology prices and constant, but no-zero WTP) and Scenario 5 (5% rise in WTP and 5% drop in technology prices). Traffic sign recognition is the least adopted and least interesting Level 1 technology in 2015, and is anticipated to remain least adopted, with adoption rates of 38.1% in 2045 in Scenario 3, but the fourth-least adopted (out of nine, excluding ESC), with adoption rates of 70% in Scenario 5[30]. The opinion summaries suggest that blind-spot monitoring and emergency automatic braking are the two most interesting Level 1 technologies for Americans; and these are anticipated to be the most and second-most adopted Level 1 technologies (excluding ESC) in 2045 in Scenario 3, with adoption rates of 53.5% and 51.2%; however these are the third-most and most adopted Level 1 technologies in Scenario 5, with adoption rates of 73.6% and 77.8%. Pedestrian detection is the second-least adopted

[30] Lane centering is the least adopted Level 1 technology in Scenario 5 in 2045, with adoption rate of 59.8%.

technology in 2015, but is expected to be the second-most adopted Level 1 technology (out of nine, excluding ESC) in 2045 in Scenario 5, with an adoption rate of 74.0%.

10.3.4 Adoption Rates of Advanced Automation Technologies

It is interesting to note that as WTP-increase-rate and technology price-drop-rates increase, Level 4 automation' adoption rates shoot up while, at the same time, Level 3 automation' adoption rate decrease. For example, in 2045, Level 3 and Level 4 adoption rates are forecasted to be 8.2% and 43.2% in Scenario 5 (5% drop in technology prices and 5% WTP rise), which change to 2.9% and 87.2% in Scenario 8 (10% drop in technology prices and 10% WTP rise). This trend occurs because the simulation framework first checks whether a new-vehicle-buyer household can afford Level 4 automation (WTP ≥ price of the technology) in that specific year. If household can, then Level 4 automation is added to the new vehicle, otherwise the same rule is checked for Level 3. So, with the increase in WTP or/and reduction in technology prices, many households will be able to afford Level 4 automation and thus, due to this hierarchical framework, Level 3 automation is automatically skipped from their choice sets. Self-parking valet system is likely to be adopted by 34.0% to 54.6% of the vehicle-fleet by 2030 and 67.1% to 99.4% of the vehicle-fleet by 2045[31].

[31] The lower bounds on adoption rate comes from a 5% drop in technology prices and 5% WTP rise and upper bound is forecasted via a 10% drop in technology prices and 10% increase in WTP values.

Chapter 11: Conclusions

These survey results offer insights about Americans' current adoption of, WTP for, and interest in CAV technologies, while helping traffic engineers, planners and policymakers forecast long-term (year 2015 to 2045) adoption of these technologies under eight different scenarios based on: 5% and 10% annual drops in technology prices; 0%, 5%, and 10% annual increments in Americans' willingness to pay (WTP); and changes in government regulations (e.g., mandatory adoption of connectivity on new vehicles).

Fleet evolution results indicate that around 98% of U.S.'s vehicle-fleet is likely to have ESC and connectivity in year 2025 and 2030, respectively, under NHTSA's current and probable regulations. These regulations are likely to accelerate adoption of these technologies by 15 to 20 years, and make U.S. roads safer. In all scenarios with at least 10% WTP increment rate or at least 10% price reduction rate, all Level 1 technologies are estimated to have more than 90% adoption rates in 2045. Among Level 1 technologies, traffic sign recognition is the least interesting (54.4% of respondents reported $0 WTP) for Americans, currently the least adopted (2.1%), and is anticipated to remain least adopted, with adoption rates of 38.1% in 2045 at 5% technology price reduction and constant WTP. At 5% price reduction and 5% WTP increment rate, however, traffic sign recognition is estimated to be the fourth-least adopted, with adoption rates of 70%. Blind-spot monitoring and emergency automatic braking are the two most interesting Level 1 technologies for Americans; and they are anticipated to be the most and second-most adopted Level 1 technologies (excluding ESC) in 2045 at 5% technology price reduction and constant WTP, with adoption rates of 53.5% and 51.2%; however these are anticipated to be third-most and most adopted Level 1 technologies in 2045 at 5% price reduction and 5% WTP increment rate, with adoption rates of 73.6% and 77.8%.

More than half of the respondents are not willing to pay anything to add the advanced automation technologies (self-parking valet, and Level 3 and Level 4 automation). Thus, the population-weighted average WTP to add these technologies is less than half of the average WTP of the respondents who indicate non-zero WTP for these technologies. Of the respondents with a non-zero WTP, the average WTP to add connectivity and Level 3 and Level 4 automation are $110, $5,551, and $14,589, respectively. Long-term fleet evolution suggests that Level 4 AVs are likely to represent 24.8% to 87.2% of vehicle fleet in 2045[32]. Overall, simulations suggest that, without a rise in most people's WTP, or policies that promote or even require technologies, or unusually rapid reductions in technology costs, it is unlikely that the U.S. light-duty vehicle fleet's technology mix will be anywhere near homogeneous by the year 2045.

These results reflect the current perceptions of Americans. As the public learns more about CAVs and more technological experiences start spilling into the public domain, these perceptions, and potential behavioral responses are apt to change. For example, a large proportion (more than 50%) of individuals who do not want to pay anything for advanced automation technologies may change their perspectives, as the technology becomes proven and they see their neighbors, friends and co-workers adopt AVs to great success. Alternatively, a well-publicized catastrophe (such as a multi-vehicle, multi-fatality cyber-attack) could set adoption rates back years.

WTP is typically a function of demographics and built-environment factors and thus is expected to change over the years. Since this study does not consider the evolution

[32] The lower-bound on adoption rate comes from a 5% drop in technology prices and constant WTP, and the upper bound is forecast via a 10% drop in technology prices and 10% increase in WTP values.

of a household's demographic and built-environment characteristics (e.g., change in household size, number of workers, and neighborhood population density), household's WTP over time is considered to increase at constant annual rates. However, integration of household evolution over the years, followed by behaviorally-defensible temporal variation in the households' WTP, can change the estimates of the technology adoption rates. This is a potential future research direction. Lastly, SAVs are likely to change future vehicle ownership patterns and thus, inclusion of them in the simulation framework can be a good extension of this study.

PART 3: ASSESSING PUBLIC OPINIONS OF AND INTEREST IN NEW VEHICLE TECHNOLOGIES: A TEXAS PERSPECTIVE

Chapter 12: Introduction and Motivation[33]

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

CAVs are no longer a fantasy, and may soon become a daily mode of transport for hundreds of millions of people. Several mainstream companies such as Google, Toyota, Nissan, and Audi are developing and testing their own prototypes (Smiechowski 2014). With rapid advances in vehicle automation and connectivity, the U.S. National Highway Traffic Safety Administration (NHTSA 2013 & 2014a) has recognized key policy needs for CAVs. California, Nevada, Florida, and Michigan states have legislation to allow AV testing on public roads (Schoettle and Sivak 2014a). Navigant Research (2014) estimated that 75% of all light-duty-vehicle sales around the globe (almost 100 million annually) will be autonomous-capable by 2035. In accordance with this timeline, Litman (2015) expects that AVs' beneficial impacts on safety and congestion are likely to appear

[33] A publishable manuscript based on this part of thesis is under preparation with Kara Kockelman (Bansal and Kockelman 2015b).

between 2040 and 2060. If AVs prove to be very beneficial, Litman (2015) suggests that human driving may be restricted after the 2060.

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

This study designed and disseminated a survey for adult residents of Texas and received 1,088 completed responses. Those data facilitate a variety of perception and attitude analyses, using various econometric models. Response variables include respondents' WTP to add different Levels of automation and connectivity; adoption rates of shared AVs under different pricing scenarios; adoption timing of CAV technologies; home location decisions after AVs become a common travel mode; and support for road-tolling policies (to avoid excessive demand from easier travel). Motivations for each behavioral model are provided below.

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

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

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

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

Reliable availability of low-cost SAVs (with an option of DRS) may increase the shared vehicle market and reduce private-vehicle ownership. However, such high levels of service may induce demand for more VMT (Anderson et al. 2014). Tolling policies can moderate such rebound and congestion potential. Thus, this study also explores the factors affecting individuals' opinions about tolling policies more generally. The following sections describe related literature, survey's design, many summary statistics, choice model specifications, key findings, and study conclusions.

Chapter 13: Literature Review

This chapter summarizes the key findings of recent public opinion surveys about adoption of CAVs. Casley et al. (2013) conducted a survey of 467 respondents to understand their opinion about AVs. The results indicate that approximately 30% of respondents were willing to spend more than $5,000 to adopt full automation to their next vehicle purchase and around the same proportion of respondents showed interest in adopting AV technology, four years after its introduction in the market. Eighty-two percent of respondents reported safety as the most important factor affecting their adoption of AVs, 12% said legislation, and 6% said cost.

Begg (2014) conducted a survey of over 3,500 London transport professionals to understand their expectations and issues related to the growth of driverless transportation in London. Eighty-eight percent of respondents expected Level 2 vehicles to be on the road in the U.K. by 2040; 67% and 30% believe the same for Level 3 and Level 4[34] vehicles, respectively. Furthermore, approximately 60% of respondents supported driverless trains in London, and the same proportion of respondents expected AVs to be safer than conventional vehicles.

Kyriakidis et al. (2014) conducted a survey of 5,000 respondents across 109 countries by means of a crowd-sourcing internet survey. Results indicate that respondents with higher VMT and who use the automatic cruise control feature in their current vehicles are likely to pay more for fully-automated vehicles. Approximately 20% of respondents showed a WTP of more than $7,000 for Level 4 AVs, and approximately the same proportion of respondents did not want to pay more to add this technology to their

[34] NHTSA (2013) defined five levels of automation. To state briefly, automation Levels 0, Level 1, Level 2, Level 3, and Level 4 imply no automation, function-specific automation, combined function automation, limited self-driving automation, and full self-driving automation, respectively.

vehicle. Most importantly, 69% of respondents expected that fully-automated vehicles are likely to gain 50% market share by 2050.

Schoettle and Sivak (2014a) surveyed 1,533 respondents across the U.K., the U.S., and Australia to understand their perception about AVs. Results indicate that approximately two-thirds of respondents had previously heard about AVs. When respondents were asked about the potential benefits of Level 4 AVs, 72% expected fuel economy to increase, while 43% expected travel time savings to increase. Interestingly, 25% respondents were willing to spend at least $2,000 to add full self-driving automation in the US, while same proportion of respondents in the UK and Australia were willing to spend $1,710 and $2,350, respectively. However, 54.5% respondents is the U.S., 55.2% in the U.K., and 55.2% in Australia did not want to pay more to add these technologies. When asked about their activities (e.g., work, read, and talk with friends) while riding in Level 4 AVs, highest proportion, 41%, of respondents said they would watch the road even though they would not be driving. Results of one-way analysis of variance indicated that females are more concerned about AV technologies than males.

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

CarInsurance.com's survey of 2000 respondents found that approximately 20% of respondents were interested in buying AVs (Vallet 2013). Interestingly, when respondents were presented with an 80% discount on car insurance for AV owners, 34% and 56 % of respondents indicated strong and moderate interest in buying AVs, respectively. When respondents were asked to choose the activities they would like to perform while riding in AVs, the highest share of respondents (26%) chose to talk with friends. Survey results also indicate that approximately 75% of respondents believed that they could drive more safely than AVs. Only 25% would allow their children to go school in AVs, unchaperoned. When asked who they would trust most to deliver the AV technology, highest proportion (54%) of respondents said traditional automobile companies (e.g., Honda, Ford, and Toyota), instead of other companies (e.g., Google, Microsoft, Samsung, and Tesla). Seapine Software's (2014) survey of 2,038 reported that approximately 88% of respondents (84% of 18 to 34 year-olds and 93% of 65 year-olds), were concerned about riding in AVs. Seventy-nine percent of respondents were concerned about AV equipment failure, while 59% and 52% were concerned about liability issues and hacking of AVs, respectively.

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

A KPMG (2013) focus group study, using 32 participants, notes that respondents became more interested in AVs when they were provided incentives like a designated lane for AVs, and learned their commute time would be cut in half. In contrast to Schoettle and Sivak's (2014a) findings, the focus group's discussion and participants' ratings for AV technology suggests that females are more interested in these technologies than males. While focus-group females emphasized the benefits of self-driving vehicles (e.g., mobility for physically challenged travelers), males were more concerned about being forced to follow speed limits. Interestingly, the oldest participants (60 years old+) and the youngest (21 to 34 year-olds) expressed the highest WTP in order to obtain self-driving technologies. Continental (2015) surveyed 1,800 and 2,300 respondents in Germany and the United States, respectively. Approximately 60% of respondents expected to use AVs in stressful driving situations, 50% believed that AVs can prevent accidents, and roughly the same number indicated they would likely engage in other activities while riding in AVs.

Recently, Schoettle and Sivak (2014b) surveyed 1,596 respondents across the U.K, the U.S., and Australia to understand their perception about CVs. Surprisingly, only 25% of respondents had heard about CVs. When asked about the expected benefits of CVs, the highest proportion, 85.9%, of respondents expected fewer accidents and the lowest proportion, 61.2%, expected less distraction for the driver. Approximately 84% of respondents rated safety as the most important benefit of CVs, 10% said mobility, and 6% said environmental benefits. Interestingly, 25% respondents were willing to spend at least \$500, \$455, and \$394 in the U.S., the U.K, and Australia, respectively, to add CV technology. However, 45.5%, 44.8%, and 42.6% of respondents did not want to pay anything extra to add these technologies in the U.S., the U.K., and Australia, respectively.

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

Chapter 14: Survey Design and Data Processing

14.1 Questionnaire Design and Data Acquisition

A Texas-wide survey was designed and disseminated in June 2015 using Qualtrics, a web-based survey tool. The Survey Sampling International's (SSI, an internationally recognized and highly professional survey firm) continuous panel of respondents served as the respondents for this survey. The Office of Research Support at The University of Texas at Austin processed this study and determined it as "Exempt" from Institutional Review Board (IRB) review (protocol number: 2014-09-0078).

Exploring respondents' opinions and preferences for the adoption of emerging vehicle and transport technologies, the survey asked 93 questions, divided into 7 sections. Respondents were asked about their opinions about AVs (e.g., concerns and benefits of AVs), crash history and opinions about speed regulations[35] (e.g., number of moving violations, and support for red light cameras and automated speed enforcement), WTP for and interest in various Level 1 and 2 technologies (e.g., adaptive headlights and adaptive cruise control). Respondents were also asked about their WTP for and interest in CVs (e.g., road sign information using a head-up display), adoption rates of carsharing, ridesharing, and SAVs, their households' home-location shifting decisions (once AVs and SAVs become common modes of transport), opinions about congestion pricing strategies (e.g., toll if revenue is evenly distributed among residents), travel patterns (e.g., AVs' usage by trip purpose and distance from city's downtown), and demographics.

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

14.2 Data Cleaning and Sample Correction

A total of 1,297 Texans completed the survey, but after removing the fast responses and conducting some sanity checks[36], 1,088 responses remained eligible for further analysis. The sample over-represented specific demographic classes, such as men older than 65 years and bachelor degree holders, and under-represented others, such as individuals who did not complete high school and 18 to 24 years old men. Therefore, the survey sample proportions in three demographic classes or sixty categories (two gender-based, five age-based, and six educational-attainment groups) were scaled using the 2013 American Community Survey's PUMS (2013) for Texas[37]. These scale factors were used as person-level weights to un-bias person-related summary statistics (e.g., concerns related to AVs) and model-based parameter estimates (e.g., binary opinion whether allow a 13 to 15 year old child to ride alone in AVs or not).

Similarly, some household groups were under- or over-represented. Thus, household weights were calculated for 3 demographic classes or twenty-six categories (4 household size groups, 4 household workers groups, and 2 vehicle ownership groups)[38] using PUMS 2013 data. These household weights were used to un-bias household-related

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

[37] Two categories "Master's degree holder female and 18 to 24 years old" and "Master's degree holder male and 18 to 24 years old" were missing in the sample data. These categories were merged with "Bachelor's degree holder female and 18 to 24 years old" and "Bachelor's degree holder male and 18 to 24 years old", respectively, in the population.

[38] There are 32 combinations of traits (4 x 4 x 2 = 32), but there are only 26 categories because some of the categories cannot exist. For example, the number of workers cannot exceed household size. A category "household with more than 3 members, more than 2 workers, and no vehicle" was missing and was merged with "household with more than 3 members, 2 workers, and no vehicle" in the population.

(e.g., WTP for new technologies and vehicle transaction decisions) model estimates and summary statistics.

14.3 Geocoding

To understand the spread of survey respondents across Texas and to account for the impact of built-environment factors (e.g., population density and population below poverty line) on respondents WTP for and opinion about CAV technologies, the respondents' home addresses were geocoded using Google Maps API and spatially joined with Texas's census-tract-level shape file using open-source Quantum GIS. 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. Figure 14.1 shows the geocoded respondents across Texas, with most respondents living in or around Texas' biggest cities (Houston, Dallas, Fort Worth, San Antonio, and Austin), as expected in a relatively unbiased sample.

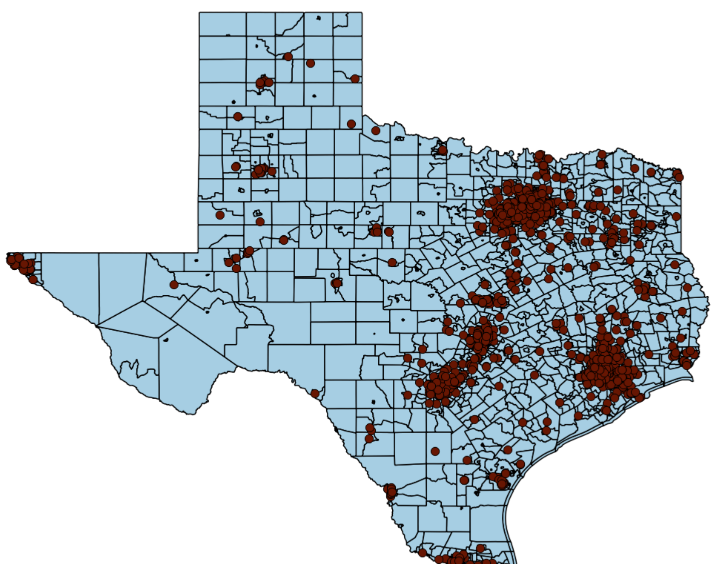

Figure 14.1: Geocoded Respondents across Texas

Chapter 15: Dataset Statistics

Table 15.1 summarizes the all explanatory variables used in the several model calibrations of this study. These are grouped into six categories: person-, household-, location-, travel-, technology-, and safety-based predictors. Person- and household-based weights, as appropriate, were employed in calculating summary statistics and model calibration to correct for sample biases.

15.1 Texans' Technology-awareness and Safety-related Opinions

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

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

Table 15.1: Population-weighted Summary Statistics of Covariates (N_{obs}=1,088)

Type	Explanatory Variable	Mean	SD	Min.	Max.
Person-based Predictors	Licensed driver (number of years)	19.11	12.50	0	32.5
	Licensed driver for more than 20 years	0.51	0.50	0	1
	Have U.S. driver license?	0.86	0.35	0	1
	Age of respondent (years)	44.56	16.31	21	69.5
	Younger than 34 years?	0.34	0.47	0	1
	Older than 54 years?	0.33	0.47	0	1
	Ethnicity: White, European white or Caucasian?	0.59	0.49	0	1
	Marital Status: Single?	0.33	0.47	0	1
	Marital Status: Married?	0.49	0.50	0	1
	Gender: Male?	0.49	0.50	0	1
	No disability?	0.90	0.09	0	1
	Bachelor's degree holder?	0.25	0.43	0	1
	Employment: Unemployed?	0.22	0.42	0	1
	Employment: Full time worker?	0.34	0.47	0	1
Household-based Predictors	Household size over 3?	0.27	0.45	0	1
	Household income ($)	59,506	46,843	5,000	225,000
	Household income is less than $30,000?	0.28	0.45	0	1
	Household size	2.62	1.43	1	9
	Number of workers in household	1.21	0.89	0	6
	More than one worker in household?	0.36	0.48	0	1
	Own at least one vehicle?	0.94	0.24	0	1
	Number of children in household	0.62	1.05	0	6
Location-based Predictors	Distance between home and public transit stop (miles)	6.12	6.20	0.5	17.5
	Distance between home and city's downtown (miles)	9.59	5.97	0.5	17.5
	Home and city's downtown are more than 10 miles apart?	0.47	0.50	0	1
	Distance from city center (miles)	9.85	7.46	0.5	25
	Employed and over 16 years of age (per square mile)	2,536	2,619	0	20,384
	% of families below poverty line in the census tract	13.01	11.20	0	100
	Population density (per square mile)	3,253	3,366	1	32,880
Travel-based Predictors	Drive alone for work trips?	0.51	0.50	0	1
	Number of personal business trips in past 7 days	1.58	2.26	0	9.5
	More than 2 personal business trips in past 7 days?	0.20	0.40	0	1
	Number of social (or recreational) trips in past 7 days	2.25	2.23	0	9.5
	More than 2 social (or recreational) trips in past 7 days?	0.31	0.46	0	1
	Annual VMT (miles)	8,607	6,391	1,500	22,500
	Annual VMT is more than 15,000 miles?	0.17	0.38	0	1

Table 15.1 (continued)

Tech-based Predictors	Carry a smartphone?	0.77	0.42	0	1
	Have heard about Google car?	0.59	0.49	0	1
	Familiar with UberX or Lyft?	0.64	0.48	0	1
	Have heard about CVs?	0.19	0.15	0	1
	Familiar with carsharing?	0.25	0.44	0	1
	Own at least a vehicle with Level 2 automation?	0.07	0.26	0	1
Safety-based Predictors	Support the use of Red Light Camera?	0.54	0.50	0	1
	Support the use of Automated Speed Enforcement?	0.52	0.50	0	1
	Support the use of Speed Governors on all new vehicles?	0.48	0.50	0	1
	Number of fatal (or serious) crashes in past 15 years	0.28	1.43	0	16
	At least one fatal (or serious) crash in past 15 years	0.08	0.27	0	1
	Number of crashes with only monetary loss in past 15 years	0.70	1.87	0	18
	Number of moving violations in past 10 years	0.97	2.23	0	26
	More than one moving violation in past 10 years?	0.20	0.40	0	1

15.2 Key Response Variables

Table 15.2 shows respondents' opinions about and average WTP for different automation Levels and connectivity. Texans valued Level 2, Level 3, and Level 4 automation at $2,910, $4,607, and $7,589, on average; in contrast, 54.4%, 31.7%, and 26.6% of Texans are not willing to pay more than $1500 for these technologies, respectively. As expected, average WTP increases with Level of automation. Interestingly, around half of Texans' (47%) AV adoption timings of AVs are dependent on their friends' adoption rates[39].

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

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

Table 15.2: Population-weighted Results of WTP for and opinion about Connectivity (1,063)[40] and Automation Technologies (N_{obs}=755)[41]

Response Variable	Percentages	Mean	SD	Min.	Max.
WTP for Adding Connectivity		$127	$164	$0	$1,100
$0	29.3%				
$1 to $99	28.1%				
$100 to $199	20.4%				
$200 to $299	11.2%				
$300 or more	11.0%				
WTP for Adding LV 4 Automation		$7,589	$7,628	$750	$31,500
Less than $1,500	26.6%				
$1,500 to $5,999	28.7%				
$6,000 to $11,999	13.6%				
$12,000 or more	31.1%				
WTP for Adding LV 3 Automation		$4,607	$5,421	$750	$31,500
Less than $1,500	31.7%				
$1,500 to $2,999	24.5%				
$3,000 to $5,999	21.4%				
$6,000 or more	22.4%				
WTP for Adding LV2 Automation		$2,910	$4,312	$750	$31,500
Less than $1,500	54.4%				
$1,500 to $2,999	23.3%				
$3,000 or more	22.3%				
Adoption timing of Level 4 AVs		**Response Variable**			**Percentages**
Never	39%	*Interest in adding connectivity*			
When 50% friends adopt	32%	Not interested			26%
When 10% friends adopt	15%	Neutral			35%
As soon as available	14%	Interested			39%

Table 15.3 shows respondents' opinions about SAV adoption rates in different pricing scenarios and home-location shifting decisions when AVs and SAVs become common modes of transport. Around 41% of Texans are not ready to use SAVs and only 7.3% hope to rely entirely on SAV fleet, even at $1 per mile. AVs and SAVs are less likely to affect Texans' decisions about moving closer to or farther from the city center:

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[40] The questions about interest in and WTP for connectivity were only asked to the respondents (1,063 out of 1,088 respondents) who either have at least a vehicle or are planning to buy a vehicle in the next 5 years.

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

about 81.5% indicated their intention to stay at their current locations. It is interesting that Texans' support for different congestion pricing policies do not vary much, on average. However, among three policies, most Texans (37.3%) support tolling congested highways if the resulting revenue can be used to lower property taxes.

Table 15.3: Population-weighted Opinions about SAV Adoption Rates, Congestion Pricing, and Home Location Shifting (N_{obs}=1,088)

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

15.3 Opinions about AVs

Table 15.4 suggests that only 28.5% of Texans are not interested in owning or leasing Level 4 AVs (if affordable), indicating that they are excited about self-driving cars. Respondents were asked about the activities they believe they will perform while riding in a self-driving vehicle; talking to other passengers (59.5%) and looking out the window (59.4%) were two most popular responses[42]. Among those Texans who are interested in AVs, most would let their vehicle drive itself on freeways (60.9%) and in scenic areas (58.6%), but they are least comfortable riding in AVs on congested streets (36.1%). Among those who indicated interest in using self-driving vehicles, 33.9% are interested in using AVs for all trip types and 24.7% indicated interest in using AVs for social or recreational trips.

Texans' average WTP to save 15 minutes of travel time on a 30-minute one-way trip is \$6.80, but this figure increases to \$9.50 if we remove those respondents with \$0 WTP for this benefit (28.5%). This result indicates that most Texans associate significant monetary value with their travel time and are ready to pay more to travel faster. More than 30% of Texans are not ready to pay anything to ride in Level 4 AVs for all three trip types (i.e., work, shopping, and intercity). Consideration of riding with families or friends is not expected to improve WTP of respondents who do not want to pay anything, but for all three trip types, average WTP is the highest while riding in AVs with families (e.g., \$7.30 for work trip) and lowest while riding alone (e.g., \$6.10 for work trip)[43]. Average WTP to ride in Level 4 AVs on a one-way trip, among those with positive WTP, is the highest for the intercity trips (\$18.10), and it increases to \$20.40 for a ride with family. However, on a per-mile scale (i.e., considering average trip length of each trip type), the average WTP to ride in AVs is the highest for the shopping trips: \$1.06 per mile for traveling alone and \$1.26 for traveling with family.

[42]Around, 45% of Texans eat or drink at least one a week while driving, but this proportion is expected to increase to 56% while riding in self-driving vehicles.
[43] However, average WTP to ride in Level 4 AVs is the same for riding alone or with the friends for work trips.

Table 15.4: Population-weighted Opinions about Level 4 Self-driving Technology (N_{obs}=1,088)

Response Variable	Percentage	Response Variable	Percentage
Interest in Level 4 AVs (if affordable)			
Not Interested	28.5%	Moderately Interested	28.6%
Slightly Interested	21.0%	Very Interested	21.9%
Activities to be Performed while riding in Level 4 AVs			
Watch movies or play games	27.3%	Sleep	18.1%
Surf the internet	33.3%	Look out the window	59.4%
Text, or talk on phone	46.2%	Exercise	7.8%
Talk to others in a car	59.5%	Maintenance activities	17.5%
Eat or drink	56.0%	Work	17.4%
Read	24.5%		
Like to Ride AVs on (N_{obs} = 863)[44]			
Freeway	60.9%	Scenic Areas	58.6%
Less congested streets	51.0%	Parking	43.6%
Congested streets	36.1%	Other	8.1%
Set Self-drive mode during (N_{obs} = 863)			
All types of trips	33.9%	Personal business trip	17.0%
Work trip	17.0%	Recreational trip	24.7%
School trip	7.0%	Shopping trip	17.9%
WTP to save 15 Minutes of Travel Time on One-way trip			
Will not pay anything	28.5%	Will pay more than $0	71.5%
WTP to Ride AVs on One-way Journey	**Ride alone**	**Ride with family**	**Ride with friends**
Will not pay anything (%)			
Work trip	41.2%	43.1%	42.7%
Shopping trip	38.6%	37.9%	39.6%
Next closest big city	30.1%	29.9%	31.6%
WTP, for All Respondents ($)			
Work trip	$5.9	$7.7	$5.9
Shopping trip	$6.1	$7.3	$6.9
Next closest big city	$12.7	$14.3	$13.4
WTP, for Those with WTP > 0 ($)			
Work trip	$10.1	$13.6	$10.3
Shopping trip	$9.9	$11.8	$11.5
Next closest big city	$18.1	$20.4	$19.6
Typical One-way Distance (miles)			
Work trip	11.29		
Shopping trip	9.38		
Next closest big city	53.11		

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

Table 15.5 summarizes key concerns and benefits of AVs. Affordability and equipment failure are the top two concerns regarding AVs; the two least concerning aspects are learning how to use AVs and, surprisingly, privacy breaches. Texans expect that AVs can help attain better fuel economy and also reduce crashes: 53.9% and 53.1% of the respondents, respectively, indicated that these benefits will be very significant.

Table 15.5: Major Concerns and Benefits Associated with AVs (N_{obs}=1,088)

Major Concerns Associated with Self Driving	**Not Worried**	**Slightly Worried**	**Very Worried**
Equipment failure	8.4%	30.2%	61.4%
Legal liability	14.2%	32.8%	52.9%
Hacking of vehicle	15.1%	29.9%	55.1%
Privacy breach	26.3%	39.0%	34.7%
Interactions with conventional vehicles	11.7%	34.5%	53.8%
Learning to use AVs	37.6%	37.7%	24.7%
Affordability	9.1%	26.4%	64.5%
Major Benefits from AVs	**Insignificant**	**Slightly Significant**	**Very Significant**
Fewer crashes	7.3%	39.6%	53.1%
Less congestion	10.8%	44.6%	44.6%
Lower emissions	11.7%	42.5%	45.7%
Better fuel economy	7.7%	38.4%	53.9%

15.4 Opinions about CVs

Table 15.6 demonstrates Texans' current usage and interest in certain connectivity features. Automated notification of emergency services in an event of an accident and vehicle health reporting are the two most interesting connectivity features for Texans; 71.5% and 68.5% of respondents are interested in these features. In-vehicle features allowing one to compose emails and surfing internet via in-built car displays are the two least interesting features; 58.1% and 51.5% of the respondents indicated no interest in these features. However, most of the features have less than 10% adoption rates, real-time traffic information and operating a smartphone using controls on a steering wheel are the two most adopted features, with current adoption rates of 15.6% and 13.4%.

Table 15.6: Current Adoption and Interest in Connectivity Features (N_{obs}=1,063) [45]

	Not Interested	Interested	Alread y Using
Real-time traffic information	22.6%	61.8%	**15.6%**
Alert about the presence of roadside speed cameras	27.6%	65.6%	6.7%
Information about nearby available parking	33.6%	61.7%	4.7%
Automatic notification to emergency personnel in the event of an accident	18.8%	**71.5%**	9.7%
Automatic monitoring of driving habits by insurance companies	49.6%	44.2%	6.2%
Personal restrictions (example: certain speed limits for teenagers)	38.4%	53.8%	7.8%
Alcohol detection	38.0%	53.8%	8.2%
Road sign information	37.4%	58.1%	4.5%
Cabin pre-conditioning	27.3%	65.6%	7.1%
Vehicle health report	19.3%	**68.5%**	12.2%
Vehicle life-cycle management	23.2%	63.5%	13.3%
Surfing the Internet via a built-in car display	**51.5%**	43.2%	5.2%
In-vehicle feature allowing to use email	**58.1%**	38.3%	3.6%
Operating a smartphone using controls on the steering wheel	38.5%	48.1%	**13.4%**

Table 15.7 shows that Texans are most likely to support adaptive traffic signal timing and least likely to support real-time adjustment in parking prices (when 80% of vehicles are connected); 64.0% and 20.5% respondents support these policies, respectively. On average, Texans rank safety as the most important and climate change as the least important area of improvement in automobile technologies.

Table 15.7: Support for CV-related Strategies and improvements in automobile technologies (N_{obs}=1,088)

	Do Not Support	No Opinion	Support
Adaptive traffic signal timing to ease congestion	13.0%	23.1%	**64.0%**
Real-time adjustment of parking prices	48.5%	31.0%	**20.5%**
Variable toll rates on congested corridors	37.3%	29.2%	33.5%
Variable speed limits based on road and weather conditions	18.3%	19.5%	62.2%
Areas of Improvement	**Average Rank**		
Safety	1.36		
Emissions (excluding greenhouse gas)	2.27		
Travel times (and congestion)	2.64		
Energy use & climate change	2.67		

[45] The questions about interest in connectivity features were only asked to the respondents (1,063 out of 1,088 respondents) who either have at least a vehicle or are planning to buy a vehicle in the next 5 years.

15.5 OPINIONS ABOUT CARSHARING AND RIDESHARING

Table 15.8 suggests that among those who have heard about carsharing, only 10% are members of carsharing-program (e.g., Zipcar and Car2Go). The members indicated that environmental friendliness and monetary savings are the two key reasons behind joining these programs. Among non-member respondents, most (75.5%) find no reason to join a carsharing program because they rely on other means of transportation. Among those who have heard about UberX or Lyft, only 12.2% actually used it at least once as a passenger. According to UberX or Lyft users, monetary and time saving are the two key reasons for using these ridesharing services. Lastly, only 16.4% of Texans are comfortable in sharing a ride with a complete stranger.

Table 15.8: Opinions about Carsharing and On-demand Taxi Services (N_{obs}=1,088)

Carsharing (Zipcar, Gar2Go)			
Heard about carsharing	25.5%		
Among those who have heard about carsharing:			
Member of Zipcar or Car2Go	9.9%	Not a member	90.1%
Why a member? (Among members)		**Why not a member? (Among non-members)**	
Saves money	68.2%	Not available where I live	25.9%
Saves time	60.0%	Inconvenient availability	21.6%
Environmentally friendly	68.7%	own a vehicle or use transit	75.5%
Necessity (I have no car)	38.6%	It is expensive	10.3%
Good back up	35.9%	Not ready to share a vehicle	27.6%
On-demand Taxi Service (UberX or Lyft)			
Heard about UberX or Lyft	64.0%		
Among those who heard about UberX or Lyft:			
Used UberX as a Passenger	12.2%		
With Whom Will be Comfortable Sharing a Ride			
With a stranger	16.4%	With close friends and family	75.9%
With a friend of a friend	39.9%	Other	2.6%
With regular friends and family	45.4%		
Among those who Have Used UberX			
Why Used UberX			
To save money	54.4%	No need to worry about parking	21.4%
To save time	47.0%	My vehicle was unavailable	16.9%
To try it out	43.3%	To avoid driving	41.6%

Chapter 16: Model Estimation

This study estimated WTP to add connectivity and different Levels of automation using an interval regression (IR) model[46]. Please see Wooldridge (2013) to explore details about IR model, which is succinctly presented here for a response variable for only interval data[47]. The key equation is as follows:

$$y_j = \beta' x_j + \varepsilon_i \tag{9}$$

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

$$\log L = \sum_{j \in C} w_j \log\left\{\varphi\left(\frac{y_{rj} - \beta' x_j}{\sigma}\right) - \varphi\left(\frac{y_{lj} - \beta' x_j}{\sigma}\right)\right\} \tag{10}$$

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

Additionally, interest in adding connectivity (if affordable), adoption timing of AVs, adoption rates of SAVs under three pricing scenarios ($1, $2, and $3 per mile), future home-location shifts (after AVs and SAVs become common modes of transport), and opinions about three congestion pricing policies were estimated using ordered probit

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46 Respondents were asked to choose WTP interval (e.g., $1500 to $2,999 to add automation) and also provided with options of "$3000 or more" and $1000 or more" in the questions about WTP to add automation and connectivity, respectively. The response variable is right censored interval data type. Interval regression is appropriate (a form of linear regression) here for modeling such data types, since it considers interval boundaries as the fixed parameters, unlike an ordered probit model.

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

(OP) specifications in Stata 12 software (Long and Freese 2006). The OP model specifications are presented here in the context of interest in CVs. The main equation for this specification is as follows (Greene 2012):

$$y_i^* = \beta' x_i + \varepsilon_i \tag{11}$$

where, subscript i denotes an individual observation; y_i^* represents the individual's latent inclination to add connectivity (if affordable); 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:

$$\Pr(\text{not interested}) = \Pr\left(y_i^* \leq \mu_1\right) \tag{12}$$

$$\Pr(\text{neutral}) = \Pr\left(\mu_1 \leq y_i^* \leq \mu_2\right) \tag{13}$$

$$\Pr(\text{interested}) = \Pr\left(y_i^* \geq \mu_2\right) \tag{14}$$

Initial model specifications included a subset of Table 15.1'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 .05 (|Z-stat| > 1.96), covariates with p-values lower than 0.32 (which corresponds to a |Z-stat| of greater than 1.0) were also kept in the final specification.

McFadden's R-Square and adjusted R-square are calculated to measure the models' goodness of fit.

16.1 Interest in and WTP to add Connectivity

Table 16.1 summarizes the OP and IR model estimates of Texans' interest in and WTP for adding connectivity to current and future vehicles. These results indicate that more experienced licensed drivers and single individuals are less interested in adding connectivity and have lower WTP for it. Men who are familiar with carsharing, support speed regulation strategies, carry smartphone, drive alone for work, make more social/recreational trips, live far away from downtown, and have higher household income, everything else held constant, are estimated to have more interest in adding connectivity (if it is affordable), but respondents living farther from transit stops are less interested.

Disable men with bachelor's degree who are familiar with ridesharing services, travel more, make more business trips, support speed governors, and encountered more moving violations and more fatal crashes in the past, all other predictors held constant, have higher WTP for adding connectivity, but older Caucasians with more member in the household are estimated to place lower value on connectivity. Perhaps, the educated, safety-seeking, and tech-savvy respondents are able to perceive the safety benefits of connectivity during their longer travels.

Table 16.1: Interest in Connectivity (Ordered Probit) and WTP for Connectivity (Interval Regression) Model Results

Covariates (Model 1: Interest in Connectivity, if Affordable)	**Coef.**	**Z-stat**
Licensed driver (number of years)	-0.032	-4.98
Support the use of Automated Speed Enforcement?	0.483	3.7
Support the use of Speed Governors on all new vehicles?	0.555	4.12
Number of fatal (or serious) crashes in past 15 years	0.407	2.08
Carry smartphone?	0.541	3
Familiar with carsharing?	0.418	2.95
Drive alone for work trips?	0.25	1.91
More than 2 social (or recreational) trips in past 7 days	0.234	1.82
Distance between home and public transit stop (miles)	-0.02	-2.02
Home and city's downtown are more than 10 miles apart?	0.17	1.35
Male?	0.298	2.24
Household income ($)	2.36E-06	1.75
Single?	-0.351	-2.25
Thresholds	**Coef.**	**Std. Dev.**
Not interested **vs.** Neutral	-0.356	0.282
Neutral **vs.** Interested	1.368	0.285
N_{obs}: 1063 **McFadden's R-Square:** 0.082 **McFadden's adjusted R-Square:** 0.070		
Covariates (Model 2: WTP for Connectivity)	**Coef.**	**Z-stat**
Intercept	151.40	4.64
Number of moving violations in past 10 years	10.01	5.96
Support the use of Speed Governors on all new vehicles?	48.37	5.04
Number of fatal (or serious) crashes in past 15 years	6.69	1.95
Number of crashes with only monetary loss in past 15 years	3.79	1.45
Familiar with UberX or Lyft?	21.03	2.04
Licensed driver (number of years)	-2.48	-3.24
Number of personal business trips in past 7 days	4.48	2.27
Annual VMT (miles)	1.95E-03	2.44
No disability?	-17.89	-1.23
Household size	-7.20	-1.90
Age of Respondent (years)	-0.99	-1.74
Male?	10.32	1.11
White, European white or Caucasian?	-19.66	-1.98
Household income ($)	5.96E-04	7.16
Bachelor's degree holder	15.03	1.52
Single?	-17.22	-1.48
sigma	138.30	-
N_{obs}: 1063 **McFadden's R-Square:** 0.038 **McFadden's adjusted R-Square:** 0.034		

16.2 WTP FOR AUTOMATION TECHNOLOGIES

Table 16.2 summarizes the IR model specifications of WTP to add Levels 2, 3, and 4 automation. As expected, intercepts in these models rise along with the increase in levels of automation. Respondents who have heard about the Google self-driving car (before taking the survey), support speed governors on all new vehicles, and have higher household income (everything else held constant) are estimated to pay more for all levels of automation. However, consistent with the findings of the *WTP for connectivity* model, older and more experienced licensed drivers are expected to place lower value on automation technologies. Perhaps older individuals are finding it difficult to conceive that CAVs are about to hit the roads and licensed drivers might be worried about sacrificing those elements of driving they find enjoyable. Individuals with higher annual VMT are willing to pay more for Level 4 automation, but that preference is inverted for those living in more densely populated neighborhoods. Those who live farther from transit stops are expected to pay less for Level 3 and Level 4 automations. Caucasians' WTP for Level 2 automation is estimated to be lower than for other ethnicities, as is the case for connectivity, implying that non-Caucasians are likely to be early adopters of CAV technologies. Interestingly, those who experienced more fatal crashes in the past are significantly interested in paying more for Level 2 and Level 3 automations (as is the case for connectivity); surprisingly, this relationship is reversed for those who are familiar with ridesharing services.

Table 16.2: WTP for Automation Technologies (Interval Regression Model Results)

Covariates (Model 1: WTP for Level 4 Automation)	**Coef.**	**Z-stat**
Intercept	10300	7.43
Have heard about Google car?	1521	2.64
Support the use of Speed Governors on all new vehicles?	1755	3.32
Have heard about CVs?	931.1	1.28
Licensed driver (number of years)	-61.07	-1.27
Distance between home and public transit stop (miles)	-75.18	-1.60
Annual VMT (miles)	9.96E-02	2.40
Age of Respondent (years)	-104.60	-2.71
Household income ($)	1.04E-02	1.81
Single?	1000	1.63
Population density (per square mile)	-0.11	-1.29
sigma	6961	-
N_{obs}: 755 **McFadden's R-Square:** 0.035	**McFadden's adjusted R-Square:** 0.029	
Covariates (Model 2: WTP for Level 3 Automation)	**Coef.**	**Z-stat**
Intercept	7179	7.17
Have heard about Google car?	1094	2.58
Support the use of Speed Governors on all new vehicles?	1229	3.27
Number of fatal (or serious) crashes in past 15 years	438.6	4.82
Familiar with UberX or Lyft?	-506.8	-1.21
Licensed driver (number of years)	-54.56	-1.52
Number of personal business trips in past 7 days	96.91	1.06
Distance between home and public transit stop (miles)	-42.49	-1.26
Distance between home and city's downtown (miles)	40.98	1.22
Age of Respondent (years)	-73.12	-2.45
Household income ($)	7.53E-03	1.79
sigma	4792	-
N_{obs}: 755 **McFadden's R-Square:** 0.044	**McFadden's adjusted R-Square:** 0.039	
Covariates (Model 3: WTP for Level 2 Automation)	**Coef.**	**Z-stat**
Intercept	5059	6.65
Have heard about Google car?	896.8	2.45
Support the use of Speed Governors on all new vehicles?	1241	3.94
Number of fatal (or serious) crashes in past 15 years	554.6	8.36
Familiar with UberX or Lyft?	-750.7	-2.24
Licensed driver (number of years)	-51.35	-1.80
Household size over 3?	-501.4	-1.57
Age of Respondent (years)	-38.91	-1.63
White, European white or Caucasian?	-467.8	-1.39
Household income ($)	5.55E-03	1.69
sigma	3743	-
N_{obs}: 755 **McFadden's R-Square:** 0.048	**McFadden's adjusted R-Square:** 0.042	

16.3 ADOPTION TIMING OF AUTONOMOUS VEHICLES

Table 16.3 summarizes OP model estimates of AV adoption timings (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). The adoption timing of disabled individuals and bachelor's degree holders who support speed-regulation strategies, are familiar with carsharing, travel more, have more than one worker in the household, and live in a neighborhood with a higher density of employed individuals, all other predictors held constant, are less likely to depend on friends' adoption rates. In contrast, the adoption timing of older, single, and Caucasian respondents who have larger households and live in more populous areas, are estimated to be more dependent on friends' adoption rates.

Table 16.3: Adoption Timing of Autonomous Vehicles (Ordered Probit Model Results)

Covariates	**Coef.**	**Z-stat**
Support the use of Automated Speed Enforcement?	0.455	1.82
Support the use of Speed Governors on all new vehicles?	0.365	1.99
Have heard about CVs?	0.362	1.52
Familiar with carsharing?	0.336	2.19
Distance between home and public transit stop (miles)	-0.051	-2.44
Annual VMT (miles)	3.13E-05	1.74
No disability?	-0.454	-1.65
Household size	-0.109	-1.69
More than 1 worker in household?	0.259	1.41
Age of Respondent (years)	-0.025	-2.53
White, European white or Caucasian?	-0.273	-1.32
Bachelor's degree holder	0.260	1.50
Single?	-0.385	-1.83
Population density (per square mile)	-1.76E-04	-1.47
Employed and over 16 years of age (per square mile)	1.96E-04	1.09
Thresholds	**Coef.**	**Std. Dev.**
Never **vs.** 50% friends adopt	-1.898	0.665
50% friends adopt **vs.** 10% friends adopt	-0.303	0.688
10% friends adopt **vs.** As soon as available	0.555	0.738
N_{obs}: 1,088 **McFadden's R-Square:** 0.059 **McFadden's adjusted R-Square:** 0.046		

These estimates appear to be consistent with the *WTP for automation technologies* model specification[48], i.e., the AV adoption timing of those who indicate higher WTP for AVs is less likely to depend on their friends' adoption rates.

16.4 SAV ADOPTIONS RATES UNDER DIFFERENT PRICING SCENARIOS

Table 16.4 summarizes the OP model estimates of SAV adoption rates (i.e., relying on an SAV fleet less than once a month, at least once a month, at least once a week, or entirely) under different pricing scenarios ($1 per mile [Model 1], $2 per mile [Model 2], and $3 per mile [Model 3]). Respondents who experienced fatal crashes in the past, support speed regulation strategies, have heard about CVs, live farther from downtown, and have more number of workers in households, all other predictors held constant, are likely to use SAVs frequently. In contrast, consistent with *WTP for automation technologies* model findings, Caucasians who are licensed (or more experienced) drivers and live farther from transit stops are estimated to use SAVs less frequently in all three pricing scenarios[49].

It is worth noting that even unemployed and lower income households (with annual household income less than $30,000) are estimated to use SAVs more frequently at $1 per mile; perhaps SAVs are affordable for these individuals at this price. Male respondents who travel more also expect to use SAVs more frequently at $1 per mile, since they can readily evaluate cost-reduction benefits at this lower price. Respondents who have experienced more moving violations in the past are expected to use SAVs

[48] As an exception, single respondents are estimated to have higher WTP to add Level 4 automation (other attributes held constant), but their adoption timing is more dependent on their friends' adoption rates.
[49] Since, household vehicle ownership is not controlled here, the respondents showing negative inclination towards SAVs, may have higher vehicle ownership, on average.

frequently at $1 and $2 per mile; perhaps they can visualize that SAVs can save them from future violations[50].

Table 16.4: SAV Adoption Rates under Different Pricing Scenarios (Ordered Probit Model Results)

Covariates (Model 1: $1 per mile)	**Coef.**	**Z-stat**
Number of moving violations in past 10 years	0.081	1.91
Support the use of Automated Speed Enforcement?	0.407	2.11
Support the use of Speed Governors on all new vehicles?	1.040	5.49
At least 1 fatal (or serious) crash in past 15 years?	0.615	1.64
Have heard about CVs?	0.501	1.64
Distance between home and public transit stop (miles)	-0.038	-2.15
Distance between home and city's downtown (miles)	0.025	1.66
Annual VMT more than 15,000 miles?	0.298	1.35
Number of workers in household	0.227	2.34
Male?	-0.257	-1.29
Have U.S. driver license?	-1.163	-3.15
White, European white or Caucasian?	-0.419	-2.13
Household income less than $30,000?	0.425	2.11
Unemployed?	0.508	2.10
Thresholds	**Coef.**	**Std. Dev.**
Will never use **vs.** Will rely less than once a month	-2.510	0.431
Will rely less than once a month **vs.** Will rely at least once a month	-0.769	0.412
Will rely at least once a month **vs.** Will rely at least once a week	0.510	0.411
Will rely at least once a week **vs.** Will rely entirely on SAV fleet	2.409	0.455
N_{obs}: 730 **McFadden's R-Square:** 0.113 **McFadden's adjusted R-Square:** 0.097		
Covariates (Model 2: $2 per mile)	**Coef.**	**Z-stat**
Licensed driver (number of years)	-0.017	-1.60
Number of moving violations in past 10 years	0.093	1.90
Support the use of Automated Speed Enforcement?	0.515	2.40
Support the use of Speed Governors on all new vehicles?	0.899	4.02
Number of fatal (or serious) crashes in past 15 years	0.179	1.62
Have heard about CVs?	0.640	2.47
Familiar with UberX or Lyft?	-0.527	-2.24

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

Table 16.4 (continued)

Drive alone for work trips?	-0.330	-1.61
More than 2 social (or recreational) trips in past 7 days	0.401	1.95
Distance between home and public transit stop (miles)	-0.057	-2.90
Distance between home and city's downtown (miles)	0.036	2.17
Number of workers in household	0.277	2.21
Older than 54 years?	-0.498	-2.05
White, European white or Caucasian?	-0.379	-1.92
Married?	-0.383	-1.98
Thresholds	**Coef.**	**Std. Dev.**
Will never use **vs.** Will rely less than once a month	-1.435	0.443
Will rely less than once a month **vs.** Will rely at least once a month	0.040	0.429
Will rely at least once a month **vs.** Will rely at least once a week	1.302	0.444
Will rely at least once a week **vs.** Will rely entirely on SAV fleet	3.191	0.536
N_{obs}: 730 **McFadden's R-Square:** 0.123	**McFadden's adjusted R-Square:** 0.108	
Covariates (Model 3: $3 per mile)	**Coef.**	**Z-stat**
Licensed driver (number of years)	-0.018	-2.28
Support the use of Automated Speed Enforcement?	0.475	2.37
Support the use of Speed Governors on all new vehicles?	0.895	4.34
Number of fatal (or serious) crashes in past 15 years	0.191	3.61
Have heard about CVs?	0.874	3.03
Familiar with UberX or Lyft?	-0.259	-1.38
Number of social (or recreational) trips in past 7 days	0.080	1.68
Distance between home and public transit stop (miles)	-0.056	-3.01
Distance between home and city's downtown (miles)	0.032	1.86
No disability?	-0.495	-1.72
Household size over 3?	0.291	1.49
Number of workers in household	0.127	1.17
White, European white or Caucasian?	-0.661	-3.40
Married?	-0.452	-2.33
Thresholds	**Coef.**	**Std. Dev.**
Will never use **vs.** Will rely less than once a month	-0.828	0.475
Will rely less than once a month **vs.** Will rely at least once a month	0.326	0.479
Will rely at least once a month **vs.** Will rely at least once a week	1.632	0.490
Will rely at least once a week **vs.** Will rely entirely on SAV fleet	3.381	0.606
N_{obs}: 730 **McFadden's R-Square:** 0.121	**McFadden's adjusted R-Square:** 0.105	

Interestingly, married respondents who are familiar with UberX, everything else held constant, are estimated to use SAVs less frequently, but those who make more social/recreation trips, are expected to use SAVs frequently at even $2 and $3 per mile (more than what carsharing companies and UberX charge). Perhaps those who know about ridesharing services are not willing to pay additional charges to enjoy SAVs' additional utilities (on top of traditional ridesharing); the vehicle ownership level (not controlled here) of married couples might be discouraging them from using SAVs at higher prices. Lastly, perhaps bigger households are likely to use SAVs as an alternative to a second vehicle and disabled individuals are able to perceive the maximum utility of SAVs, and thus both demographic groups are likely to use SAVs more frequently, even at $3 per mile.

16.5 Home Location Shifts due to AVs and SAVs

Table 16.5 summarizes the OP model estimates of respondents' home-location-shift decisions (i.e., shift closer to central Austin, stay at the same location, or move farther from central Austin)[51] after AVs and SAVs become common modes of transport. Bachelor's degree holders, single individuals, and full-time workers who support speed governors, own at least a vehicle with Level 2 automation, have experienced more fatal crashes in past, and live farther from a city center—all other attributes held constant—are likely to shift closer to the city center. Perhaps these individuals are excited about higher

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

density of low-cost SAVs near city center. However, respondents who live farther from transit stops, make more social/recreation trips, and are familiar with UberX (everything else held constant) are predicted to shift farther from the city center. Perhaps these individuals are concerned about higher land prices in the urban neighborhoods, and are keen to enjoy the benefits of moving to suburban areas after AVs and SAVs become common modes of transport.

Table 16.5: Home Location Shifts due to AVs and SAVs (Ordered Probit Model Results)

Covariates	**Coef.**	**Z-stat**
Own a vehicle?	-1.386	-3.25
Own at least a vehicle with Level 2 automation?	-1.443	-3.22
Support the use of Speed Governors on all new vehicles?	-0.466	-2.06
Number of fatal (or serious) crashes in past 15 years	-0.170	-1.75
Familiar with UberX or Lyft?	0.336	1.44
Distance from city centre (miles)	-0.068	-3.65
Drive alone for work trips?	0.291	1.20
Number of social (or recreational) trips in past 7 days	0.069	1.38
Distance between home and public transit stop (miles)	0.049	2.59
Older than 54 years?	-0.464	-2.17
Male?	-0.428	-2.03
White, European white or Caucasian?	-0.349	-1.37
Bachelor's degree holder	-0.263	-1.32
Full time worker?	-0.445	-1.65
Single?	-0.431	-1.63
Thresholds	**Coef.**	**Std. Dev.**
Shift closer **vs.** stay at the same location	-4.992	0.589
stay at the same location **vs.** shift farther	0.103	0.518
N_{obs}: 1,088 **McFadden's R-Square:** 0.112	**McFadden's adjusted R-Square:** 0.087	

16.6 SUPPORT FOR TOLLING POLICIES

Table 16.6 summarizes the OP model estimates of respondents' opinions (i.e., definitely not support, probably not support, do not know, probably support, or definitely support) about three tolling policies[52]. In Policy 1, revenue from tolled congested highways is used to reduce property taxes; in Policy 2, revenue from tolled congested highways is distributed evenly among Texans; in Policy 3, time varying tolls are enabled on all congested roadways. Results indicate that Caucasians who are licensed (or more experienced) drivers and live farther from transit stops, everything else held constant, are likely to show refusal for all tolling policies. Perhaps these individuals are concerned that they would be the primary toll payers[53], and only others would benefit from these three policies. Interestingly, bachelor's degree holders who live farther from downtown are estimated to support Policies 1 and 2; and full time workers who have more children in the household are likely to support Policies 2 and 3. Older respondents are predicted to refuse the options presented by Policies 1 and 3. Respondents whose households own at least one vehicle and live in populous areas (everything else held constant) specifically showed refusal for Policy 3, but those who live in neighborhoods with more employed individuals are likely to support this policy.

Table 16.6: Support for Tolling Policies (Ordered Probit Model Results)

Covariates (Model 1: Toll Congested Highways if Reduce Property Tax)	**Coef.**	**Z-stat**
Licensed driver for more than 20 years?	-0.462	-2.21
More than 2 social (or recreational) trips in past 7 days	0.295	1.69
Distance between home and public transit stop (miles)	-0.041	-2.53
Distance between home and city's downtown (miles)	0.030	2.09
Household size over 3?	-0.300	-1.50
Number of workers in household	0.228	2.27
Older than 54 years?	-0.474	-1.91
White, European white or Caucasian?	-0.553	-2.37
Bachelor's degree holder	0.365	2.33
Thresholds	**Coef.**	**Std. Dev.**
Definitely not support **vs.** Probably not support	-1.372	0.331

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

[53] However, individuals who travel more, all other attributes remaining equal, are likely to support tolling policies 2 and 3.

Table 16.6 (continued)

Probably not support **vs.** Do not know	-0.886	0.321
Do not know **vs.** Probably Support	0.268	0.325
Probably support **vs.** Definitely support	1.548	0.345
N_{obs}: 1,088 **McFadden's R-Square:** 0.049 **McFadden's adjusted R-Square:** 0.041		
Covariates (Model 2: Toll Congested Highways if Distribute Revenues)	**Coef.**	**Z-stat**
Licensed driver (number of years)	-0.043	-5.74
Distance between home and public transit stop (miles)	-0.051	-4.00
Distance between home and city's downtown (miles)	0.026	1.83
Annual VMT (miles)	2.63E-05	2.00
White, European white or Caucasian?	-0.460	-2.93
Number of children in household	0.160	2.05
Bachelor's degree holder	0.227	1.50
Full time worker?	0.307	1.89
Thresholds	**Coef.**	**Std. Dev.**
Definitely not support **vs.** Probably not support	-1.780	0.280
Probably not support **vs.** Do not know	-1.086	0.272
Do not know **vs.** Probably Support	0.027	0.272
Probably support **vs.** Definitely support	1.596	0.251
N_{obs}: 1,088 **McFadden's R-Square:** 0.061 **McFadden's adjusted R-Square:** 0.054		
Covariates (Model 3: Time-varying tolls on All Congested Roadways)	**Coef.**	**Z-stat**
Own a vehicle?	-0.754	-1.35
More than 2 personal business trips in past 7 days?	0.293	1.14
Distance between home and public transit stop (miles)	-0.024	-1.44
Annual VMT (miles)	1.92E-05	1.48
Age of Respondent (years)	-0.015	-1.84
Have U.S. driver license?	0.342	1.00
White, European white or Caucasian?	-0.903	-4.33
Number of children in household	0.168	1.91
Full time worker?	0.265	1.66
Population density (per square mile)	-2.51E-04	-1.41
Employed and over 16 years of age (per square mile)	3.96E-04	1.83
Thresholds	**Coef.**	**Std. Dev.**
Definitely not support **vs.** Probably not support	-2.486	0.492
Probably not support **vs.** Do not know	-1.949	0.498
Do not know **vs.** Probably Support	-0.411	0.508
Probably support **vs.** Definitely support	1.185	0.539
N_{obs}: 1,088 **McFadden's R-Square:** 0.057 **McFadden's adjusted R-Square:** 0.048		

Chapter 17: Conclusions

Results offer insights about Texans' WTP for CAV technologies, adoption timing of AVs, home location shifting decisions, adoption rates of SAVs, and opinions about congestion pricing strategies, among many others. The key opinion statistics indicate that around 41% of Texans are not ready to use SAVs and only 7.3% hope to rely entirely on SAV fleet, even at $1 per mile. AVs and SAVs are less likely to affect Texans' decisions about moving closer to or farther from the city center: about 81.5% indicated willingness to stay at their current locations. Talking to other passengers and looking out the window are the Texans' top two activity-picks while riding in Level 4 AVs. Affordability and equipment failure are the Texans' top two concerns regarding AVs; the two least concerning aspects are learning how to use AVs and, surprisingly, potential privacy breaches. Texans expect that AVs can help provide better fuel economy and also decrease crashes: 53.9% and 53.1% of the respondents, respectively, indicated that these benefits will be very significant.

Texans' average WTP to save 15 minutes of travel time on a 30-minute one-way trip is $6.80, but this figure increases to $9.50 if we remove those respondents with $0 WTP for this benefit (28.5%). Among those with positive WTP, the average WTPs to ride in Level 4 AVs alone on a one-way trip are $9.90, $10.10, and $18.10 for the shopping, work, and intercity trips, respectively, and these WTPs increase to $11.80, $13.60, and $20.40 for a ride with family. Texans are most likely to support adaptive traffic signal timing and least likely to support real-time adjustment in parking prices (when 80% of vehicles are connected). On average, Texans rank safety as the most important and climate change as the least important area of improvement in automobile technologies.

Additionally, to understand the impact of Texans' demographics, built-environment factors, travel characteristics, and other attributes on their adoption of and interest in CAV technologies and SAVs, ordered probit (OP) and interval regression (IR) models were estimated. The models' specifications suggest that those who support speed regulation strategies (e.g., speed governor on all new vehicles), and have higher household income, other attributes held constant, are estimated to pay more for all Levels of automation and connectivity. However, older and more experienced licensed drivers are expected to place lower value on these technologies. Perhaps older individuals are finding it difficult to conceive that CAVs are about to hit the roads and licensed drivers might be worried about sacrificing those elements of driving they find enjoyable. Caucasians' WTP for Level 2 automation and SAV adoption rates are estimated to be lower than for other ethnicities, as was the case for connectivity, implying that non-Caucasians are likely to be early adopters of these technologies. Interestingly, AV adoption timing of those who have higher WTP for AVs is less likely to depend on friends' adoption rates. It is worth noting that even unemployed and lower income households (with annual household income less than $30,000) are estimated to use SAVs more frequently at $1 per mile; perhaps SAVs are affordable for these individuals at this price. Respondents who are familiar with UberX are estimated to use SAVs less frequently at $2 and $3 per mile (more than what carsharing companies and UberX charge). Perhaps those who know about ridesharing services are not willing to pay additional costs to enjoy SAVs' additional utilities (on the top of traditional ridesharing). Bachelor's degree holders, single individuals, and full-time workers who support speed governors, own at least one vehicle with Level 2 automation, have experienced more fatal crashes in past, and live farther from a city center, all other attributes held constant, are likely to shift closer to the city center. Perhaps these individuals are excited about higher density of low-cost SAVs near city center.

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

PART 4: ASSESSING PUBLIC OPINIONS OF AND INTEREST IN NEW VEHICLE TECHNOLOGIES: AN AUSTIN PERSPECTIVE

Chapter 18: Background and Motivation[54]

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

To appreciate the difference in state's and regional perspective about CAV technologies, this study conducts similar survey (as did for Texas in part 3 of this thesis) for adult Austinites and estimates similar models[55]. The following sections describe related survey's design, many summary statistics, choice model specifications, key findings, and study conclusions.

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[54] A paper based on this part of thesis is under review for publication in *Transportation Research Part C* (submitted first revisions in August 2015), with Kara Kockelman and Amit Singh as co-authors (Bansal et al. 2015b). Kara Kockelman supervised the research and Amit Singh helped in developing summary statistics.

[55] Response variables include respondents' WTP for Level 3 AVs, Level 4 AVs, and CVs; adoption rates of shared AVs under different pricing scenarios; adoption timing of CAV technologies; home location decisions after AVs become a common travel mode; and support for road-tolling policies (to avoid excessive demand from easier travel).

Chapter 19: Survey Design and Data Processing

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

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

Chapter 20: Data Set Statistics

Table 20.1 summarizes the demographic, built-environment, zone-level[56], and technology-related variables after correction for biased-sample's demographics. This study uses these variables as the predictors in many model specifications. Prior to using these predictors, each respondent's record was population-weighted to provide relatively unbiased model calibration.

Table 20.1: 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 car	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

[56] 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.

20.1 Current Technology Awareness

To better understand the future adoption of smart transportation technologies and strategies, it is important to explore respondents' current awareness about them. Table 20.1 indicates that in general, Austinites are tech-savvy; 92% of the population-weighted sample carry or own a smartphone, 80% have heard of Google's self-driving car, and 60% consider anti-lock braking systems (ABS, required on all cars sold in the U.S. since September, 2011) to be a form of vehicle automation (which it is: Level 1 automation). Probably, due to popularity of carsharing (Car2Go and Zipcar) and ridesharing (UberX and Lyft) companies in Austin, 95% and 85% of respondents are familiar with both of them, respectively.

20.2 Key Response Variables

Table 20.2 summarizes the key response variables estimated in this study. At cost of more than $5,000, 24% and 57% of respondents were willing to add Level 3 and Level 4, respectively, to their next vehicle purchase. As expected, the average WTP (of the population-corrected sample) for Level 4 automation ($7,253) is much higher than that for Level 3 automation ($3,300). Apparently, AVs may not impact residential land-use patterns much, since 74% of respondents expect to stay at their current location even after AVs and SAVs become common modes of transport[57]. 30% showed interest in using AVs as soon as they are available for mass market sales in the U.S. Interestingly, approximately half of the respondents would prefer their family, friends, or neighbors to use AVs prior to their adoption. Only 15% and 3% of respondents expected to use SAVs

[57] 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.

once a week at a cost of $2 per mile and $3 per mile, respectively[58]. Reponses like these imply that most respondents are not willing to spend more for SAV use than what UberX & Lyft charge (about $1.50 per mile).

Table 20.2: 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%		
Toll if Reduce Property Tax		**Toll if Distribute Revenue**	
Do not support	37%	Do not support	49%
Neural	27%	Neural	31%
Support	36%	Support	20%

However, with social acceptance of AVs and the reliability of SAVs for longer-distance trips, future SAVs costs may fall. At a cost of $1 per mile, 41% of respondents expected to use SAVs at least once a week. Only 26% of respondents rejected a proposal

[58]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).

of adding connectivity[59] to their vehicles at a cost of less than $100. In this survey, respondents were also asked about their support to convert the very congested non-tolled highway sections into tolled roads in the following two scenarios: if tolling revenue is used to reduce local property taxes or if it is evenly distributed among all Austinites. Surprisingly, only 36% of respondents supported Policy 1 and 20% supported Policy 2.

20.3 Other Opinions about AVs and CVs

Table 20.3 summarizes the individuals' perceptions about the benefits and concerns of CAVs. 19% of respondents were not at all interested in owning Level 4 AVs. Respondents indicated three main issues regarding AVs: 50% of respondents were concerned about equipment or system failure, while 48% and 38% were concerned about interactions with conventional vehicles and affordability, respectively. Only 7% of respondents were apprehensive about learning to use AVs. 31% of respondents believe that AVs cannot help with calming congestion, making this the "least likely" AV benefit (among plausible options tested). When asked about the other three benefits (fewer crashes, lower emission, and better fuel economy), respondents considered them almost equally likely, but a reduction in crashes received maximum (63%) support. 75% of respondents indicated wanting to talk or text with friends and look out of the window while riding in AVs – making these the two most appealing tasks for respondents while traveling in Level 4 AVs. More than 70% of respondents would like to ride in AVs on freeways, high-speed highways, and congested traffic, while only 46 % would let the vehicles drive themselves on city streets. Surprisingly, only 47% of respondents have heard about CVs. It is worth noting that only 4.3% of respondents are currently surfing

[59]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.

internet and 6.2% are emailing while driving (conventional vehicles), but 31.7% and 39% are interested in adding these technologies to their vehicles, respectively.

Table 20.3: 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%	
Opinion about CV Technology		**Yes**	**No**	
	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%

20.4 Opinions about Carsharing and Ridesharing

Table 20.4 summarizes opinions regarding adoption of carsharing (Car2Go or Zipcar) and ridesharing (UberX or Lyft). 14.8% of respondents were a member of a carsharing program at the time of the survey (Fall of 2014).

Table 20.4: Population-weighted Results of Opinion-based Questions on Carsharing and Ridesharing

Type	Opinion-based questions	Yes	No	Skipped
	Carsharing program member	14.8%	80%	5.2%
A carsharing member because	Program saves money	6.4%	8.4%	85.2%
	Program saves time	6.2%	8.6%	85.2%
	Environment friendly program	7.1%	7.7%	85.2%
	Do not own a vehicle	1.8%	13%	85.2%
	"Other" reasons include convenient parking and ridesharing for one-way trips, back-up when car is service garage and 2nd vehicle for a two-worker family or families with more workers than vehicles.			
Not a carsharing member because	Unreliable car availability	5.2%	74.8%	20%
	Not available near home	14%	66%	20%
	Own a vehicle	66%	14%	20%
	Relay on transit or walking	41%	39%	20%
	Costly	16%	64%	20%
	Other stated reasons include inadequate capacity, fleet looks unsafe, no parking near office.			
	Used UberX or Lyft as a passenger	27%	61%	12%
Used Uber because	Saves time	17%	10%	73%
	Saves money	13%	14%	73%
	To avoid drive after drinking	14%	13%	73%
	To try it out	16%	11%	73%
		Yes	**No**	
Comfort in ridesharing	Stranger for short duration (in day-time)	51%	49%	
	Friend of one of my Facebook friends (never met before)	53%	47%	
	Regular friends & family	90.8%	9.2%	
	"Other" responses include being comfortable with approved member of car sharing community and pre-scanned cab driver of authentic company.			

Note: N_{obs}=347. In the survey, carsharing and ridesharing questions were dynamically designed with skip logic and conditional branching. For examples, respondents, who were not familiar with carsharing, were not asked whether they are carsharing members or not. Such responses were considered in the "Skipped" category.

Chapter 21: 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 WTP for AVs (Level 3 and Level 4) and support for tolling policies (if tolling revenue is used to reduce local property taxes, or if it is evenly distributed among all Austinites) each had two related response variables and so were jointly estimated using seemingly unrelated specifications[60] of the bivariate OP model (as described in Sajaia [2008]).

Initial model specifications included all Table 20.1'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 was not used as a statistical significance threshold here, due to the slightly limited sample size (n=347). If more sample observations were available (say n=1000), statistical significance could have improved for many explanatory variables. Explanatory variables with p-value less than .01 (|Z-stat|>2.58) are considered highly statistically significant predictors.

Practical significance is generally more meaningful than statistical significance. This study considers an explanatory variable to be practically significant if a one-standard-deviation increment in it leads to a significant shift in the response variable. In this study, response variables are probabilities of ordered choice options, so an

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

explanatory variable is considered to be practically significant if the predicted probabilities (i.e., the ΔPr_i shown in Tables 21.1 through 21.6) change by more than a factor of 1.3 or less than a factor of 0.7. In other words, there is at least 30 percent shift in the predicted probability (which could be from 0.50 to 0.67 or to 0.35). If the shift in the model-predicted probability exceeds 50 percent (i.e., the ratio of the two is more than 1.5 or less than 0.50), the explanatory variable is defined here as *highly* practically significant. McFadden's R-Square and adjusted R-square are also provided, to characterize all models' goodness of fit.

21.1 WILLINGNESS TO PAY FOR AVS

Table 21.1 summarizes the bivariate OP model estimates of WTP for adding Level 4 automation (of less than $2,000, $2,000 to $5,000, $5,000 to $10,000, or more than $10,000) and WTP for Level 3 automation (less than $2,000, $2,000 to $5,000, or more than $5,000). Results indicate that male respondents with a greater number of children, living in higher- income neighborhoods, and who drive alone for social trips, ceteris paribus, are willing to pay more to add Level 3 and Level 4 automation to their next vehicle. In contrast, licensed drivers living in more jobs-sense neighborhoods, and who are familiar with carsharing and ridesharing companies are estimated to pay less to add Level 3 and Level 4 automation to their next vehicles, ceteris paribus[61]. Perhaps individuals who are familiar with carsharing and ridesharing would rather rely on low-cost SAVs instead of buying a new vehicle with added automation technology.

[61] 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.

Table 21.1: 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%
Drive alone for work trips (1=yes)	0.616	1.72	-28.8%	-6.2%	7.5%	**31.1%**
Drive alone for social trips (1=yes)	0.833	2.28	-25.6%	-8.0%	8.6%	28.1%
Log(Annual VMT)	0.329	1.39	-20.2%	-15.7%	7.5%	**32.7%**
Distance from workplace (miles)	0.087	**2.96**	-22.3%	-13.9%	16.6%	27.3%
Gender (1=male)	0.442	1.28	-18.2%	-4.0%	5.7%	21.6%
U.S. driver license (1=yes)	-1.159	-1.36	18.3%	1.6%	-6.8%	-18.0%
Number of children	0.341	1.66	-15.5%	-16.4%	7.6%	21.7%
Age	-0.039	**-4.02**	**53.5%**	-12.4%	-21.5%	**-45.0%**
Total employment density (per mi^2)	-3.37E-04	-1.83	21.9%	3.7%	-8.2%	-21.2%
Median household income ($ per year)	7.29E-06	1.95	-23.8%	-15.8%	7.2%	**34.2%**
Thresholds	**Coef.**	**Std. Dev.**				
<$2,000 **vs.** $2,000 to $5,000	-7.401	0.386	--	--	--	--
$2,000-$5,000 **vs.** $5,000-$10,000	-6.514	0.299	--	--	--	--
$5,000-$10,000 **vs.** >$10,000	-5.503	0.447	--	--	--	--

Covariates (WTP for Level 3)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**
Number of past crash experiences	0.217	1.59	-24.1%	11.0%	**32.4%**
Carry smartphone (1=yes)	0.708	1.18	-10.5%	5.3%	16.5%
Familiar with carsharing (1=yes)	-1.631	-1.37	20.1%	-15.9%	-20.1%
Familiar with UberX or Lyft (1=yes)	-1.203	-1.49	19.9%	-10.8%	-25.8%
Drive alone for work trips (1=yes)	0.539	1.46	**-31.4%**	28.1%	26.3%
Drive alone for social trips (1=yes)	1.102	**3.08**	-15.9%	18.4%	12.9%
Log(Annual VMT)	-0.470	-1.75	25.6%	-15.8%	**-33.1%**
Distance from workplace (miles)	-0.085	**-2.83**	22.8%	-14.5%	-27.4%
Gender (1=male)	0.507	1.48	-14.4%	5.8%	25.4%
U.S. driver license (1=yes)	-1.623	-1.77	16.3%	-8.6%	-24.8%
Number of children	0.485	2.32	-20.3%	8.9%	27.4%
Age	-0.031	-2.53	**35.6%**	-26.4%	**-37.3%**
Total employment density (per mi^2)	-2.30E-05	-2.11	16.2%	-8.6%	-24.7%
Median household income ($ per year)	8.26E-06	1.79	-18.9%	7.2%	**32.2%**
Thresholds	**Coef.**	**Std. Dev.**			
<$2,000 **vs.** $2,000 to $5,000	-8.865	0.488	--	--	--
$2,000-$5,000 **vs.** >$5,000	-7.323	0.373	--	--	--
Correlation coefficient: 0.921	**McFadden's R-Square:** 0.101		**McFadden's adjusted R-Square:** 0.061		

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

Interestingly, individuals who travel more (exhibit higher annual VMT) and who live farther from their workplace exhibit higher WTP for adding Level 4 AVs, but lower

WTP for Level 3 AVs. Perhaps the opposite signs, but practical significance of both attributes for the WTP of Level 3 and Level 4 AVs reflect the individuals' perception that they would be able to use their travel time (for work, sleep, or other meaningful activities) in a Level 4 AVs, but not in Level 3 AVs. In addition, everything else equal, older persons are predicted to have a significantly lower WTP for AVs (in a practically and statistically significant sense). Perhaps they are concerned about learning to use AVs and do not trust these technologies. Practically significant and positive associations between the number of crashes experienced by an individual and their WTP for AVs indicates that such persons may be anticipating the safety benefits of AVs[62]. Respondents driving alone for work trips are estimated to have a (practically and statistically) significantly higher WTP for AVs, indicating the possibility of shifting commuters to SAV fleets in the future. A high correlation coefficient estimate across these two OP equations ($\rho = +0.921$) strongly supports the use of a seemingly unrelated bivariate OP specification here.

21.2 SAV ADOPTION RATES UNDER DIFFERENT PRICING SCENARIOS

Table 21.2 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 held constant).

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

Table 21.2: 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%
Employment status (1=full-time worker)	0.403	1.10	-11.3%	-3.2%	8.5%	20.5%
Area type (1=urban)	0.493	1.15	-13.0%	-3.8%	9.7%	15.6%
Population density (per mi^2)	2.59E-04	2.20	**-44.4%**	**-12.4%**	**32.3%**	**66.8%**
Households density (per mi^2)	-5.67E-04	-2.11	25.2%	-11.9%	-11.1%	-24.2%
Basic employment density (per mi^2)	-2.60E-04	-1.67	13.1%	6.4%	-10.0%	-26.6%
Thresholds	**Coef.**	**Std. Dev.**				
Will rely less than once a month **vs.** Will rely at least once a month	-0.043	0.577	--	--	--	--
Will rely at least once a month **vs.** Will rely at least once a week	1.246	0.122	--	--	--	--
Will rely at least once a week **vs.** Will rely entirely on SAV fleet	3.058	0.728	--	--	--	--
McFadden's R-Square: 0.120			**McFadden's adjusted R-Square:** 0.090			
Covariates (Model 2: \$2 per mile)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**	**ΔPr_4**
Have heard about Google car (1=yes)	0.821	1.37	-15.3%	11.3%	**37.9%**	17.8%
ABS form of automation (1=yes)	0.940	**2.68**	-22.1%	**34.1%**	24.7%	23.3%
Number of past crash experiences	0.155	1.02	-9.5%	8.9%	28.6%	12.5%
Familiar with carsharing (1=yes)	-2.281	-1.25	22.8%	-22.4%	**-42.1%**	**-69.5%**
Distance from workplace (miles)	0.124	**2.94**	**-40.5%**	**51.7%**	21.7%	21.3%
Household size	0.310	1.97	-16.3%	18.5%	27.6%	17.4%
Gender (1=male)	0.690	2.00	-10.5%	13.0%	15.1%	18.2%
U.S. driver license (1=yes)	-1.432	-1.98	12.3%	-11.1%	-26.6%	-24.4%
Number of children	-0.542	-1.97	13.1%	-17.7%	-24.5%	-12.1%
Age	-0.014	-1.20	25.6%	**-39.2%**	-22.5%	-18.4%
Employment status (1=full-time worker)	0.839	2.28	-15.3%	19.7%	27.9%	16.3%
Area type (1=urban)	0.694	1.36	-11.9%	10.9%	23.4%	12.7%
Population density (per mi^2)	2.64E-04	2.14	-28.4%	35.3%	**45.1%**	19.6%
Households density (per mi^2)	-6.52E-04	-2.26	17.5%	-25.3%	-22.2%	-18.8%
Basic employment density (per mi^2)	-1.82E-04	-1.12	5.4%	-5.7%	-14.5%	-15.9%
Thresholds	**Coef.**	**Std. Dev.**				
Rely less than once a month **vs.** Rely at least once a month	-1.275	0.625	--	--	--	--
Rely at least once a month **vs.** Rely at least once a week	0.468	0.448	--	--	--	--
At least once a week **vs.** Rely entirely on SAV fleet	2.425	0.819	--	--	--	--
McFadden's R-Square: 0.129			**McFadden's adjusted R-Square:** 0.079			

Table 21.2 (continued)

Covariates (Model 3: $3 per mile)	**Coef.**	**Z-stat**	**ΔPr$_1$**	**ΔPr$_2$**	**ΔPr$_3$**	**ΔPr$_4$**
Have heard about Google car (1=yes)	1.473	2.21	-10.7%	25.1%	18.0%	**36.4%**
ABS form of automation (1=yes)	1.431	**3.28**	-20.3%	**51.7%**	29.5%	17.2%
Number of past crash experiences	0.183	1.23	-11.3%	29.2%	**32.9%**	23.6%
Familiar with carsharing (1=yes)	-1.948	**-3.05**	15.3%	**-39.4%**	-21.7%	**-34.7%**
Annual VMT	-5.32E-05	-1.65	20.3%	**-52.3%**	-17.8%	-10.8%
Distance from downtown (miles)	-0.064	-1.63	10.3%	-22.7%	-22.9%	-26.1%
Gender (1=male)	0.658	1.76	-8.1%	17.8%	14.3%	15.9%
U.S. driver license (1=yes)	-1.864	-2.56	12.1%	-28.2%	-12.1%	-16.2%
Age	-0.029	-2.30	10.2%	-21.8%	-11.5%	-12.5%
Employment status (1=full-time worker)	1.022	2.49	-16.2%	**41.5%**	10.7%	26.6%
Area type (1=urban)	0.762	1.13	-10.4%	26.4%	17.7%	15.5%
Population density (per mi^2)	9.52E-05	**3.06**	-13.1%	**31.8%**	**35.1%**	17.8%
Retail employment density (per mi^2)	1.70E-04	1.20	-11.4%	27.9%	12.8%	14.4%
Service employment density (per mi^2)	-6.66E-05	**-3.10**	5.4%	-15.7%	-10.1%	-12.1%
Thresholds	**Coef.**	**Std. Dev.**				
Rely less than once a month **vs.** Rely at least once a month	-1.177	0.621	--	--	--	--
Rely at least once a month **vs.** Rely at least once a week	1.646	0.789	--	--	--	--
At least once a week **vs.** Rely entirely on SAV fleet	3.068	0.462	--	--	--	--
McFadden's R-Square: 0.171			**McFadden's adjusted R-Square:** 0.105			

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

The practically significant positive associations of indicator variables (whether an individual has heard about Google's self-driving car and if an individual thinks that ABS is form of automation), in all three pricing-scenarios, suggests that tech-savvy individuals are likely to be frequent SAV users. Similarly, those living in denser neighborhoods expect higher SAV adoption rates (in all three models), perhaps due to less convenient parking facilities and lower vehicle ownership rates in these areas (Celsor and Millard-Ball 2007). A highly practically significant and positive relationship between the home-distance from one's workplace and SAV adoption rates in Models 1 and 2 suggests that these workers are likely to use SAVs more often at current carsharing and ridesharing prices. Although this variable (respondents' distances from their workplace) does not appear in Model 3's final specification, another covariate, distance from downtown, may be capturing its effect[63]. 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.

21.3 Willingness to Pay for CVs

Table 21.3 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

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

the safety benefits of low-cost connectivity. Therefore, the corresponding predictors enjoy positive and practically significant relationships with WTP for CVs.

Table 21.3: Willingness to Pay for Connected Vehicles (Ordered Probit Model Results)

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

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

21.4 Adoption Timing of AVs

Table 21.4 summarizes the OP model estimates of the adoption timing of AVs (i.e., never adopt AVs, adopt AVs when 50% of friends adopt, when 10 % of friends adopt, or as soon as available in the market). AV adoption by older licensed drivers living farther from their workplace in high basic employment density neighborhoods, ceteris paribus, is more likely to depend on their friends' adoption rates. However, males with higher household income, living in urban neighborhoods, and who travel more, all other attributes remaining constant, are estimated to have a practically significant inclination to adopt AVs, with less dependence on their friends' adoption rates. Number of accidents experienced by the individual and the indicator variables, whether an individual has heard about Google's self-driving car and if an individual thinks that ABS is a form of automation, exhibit a positive and practically significant association with AV adoption timing. This relationship indicates that techy-savvy individuals, who perceive the safety benefits of AVs, are more likely to adopt them with less dependence on their friends' adoption rates.

Table 21.4: Adoption Timing of Autonomous Vehicles (Ordered Probit Model Results)

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

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

21.5 Home Location Shifts due to AVs and SAVs

Table 21.5 summarizes the OP model estimates of respondents' home-location-shift decisions (i.e., shift closer to central Austin, stay at the same location, or move farther from central Austin) after AVs and SAVs become common modes of transport. Results indicate that respondents with a greater number of children, living farther from their workplace in high employment density neighborhoods, and who drive alone for work trips, ceteris paribus, are predicted to shift farther from central Austin. Perhaps these individuals are excited about lower land prices in suburbs and are comfortable using their longer commute times pursuing other activities (e.g., working, talking with friends, and reading). People with Bachelor's degrees, living in high household density neighborhoods, all other attributes remaining the same, also exhibit a practically significant inclination to shift farther from central Austin. Perhaps these individuals are concerned about higher land prices in the highly populated neighborhoods, and are keen to the benefits of moving to suburban areas after AVs and SAVs become common modes of transport. In contrast, full-time working males, with higher household income and higher VMT, all other predictors remaining constant, are likely to shift closer to central Austin, perhaps to appreciate and adopt low-cost SAVs' higher level of service. As expected, tech-savvy respondents (i.e., who carry a smartphone and are familiar with carsharing options), living in urban neighborhoods, ceteris paribus, are estimated to have a practically significant propensity to shift closer to central Austin.

Table 21.5: Home Location Shifts due to AVs and SAVs (Ordered Probit Model Results)

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

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

21.6 SUPPORT FOR TOLLING POLICIES

Table 21.6 summarizes the bivariate OP model estimates of respondents' support (i.e., do not support, neutral, or support) for two tolling policies. They are Policy 1, where toll revenue is used to reduce property taxes, and Policy 2, where toll revenue is distributed evenly among Austinites. Expectedly, people with bachelor's degrees, with higher household income, ceteris paribus, are predicted to express practically significant support for both policies. However, older individuals, who drive alone to work, all other attributes remaining constant, are predicted to exhibit practically significant dissent for both tolling policies. Perhaps these individuals are concerned that they would be the leading toll payers, and only others would benefit from these two policies.

Table 21.6: Support for Tolling Policies (Bivariate Ordered Probit Model Results)

Covariates (Toll if Reduce Property Tax)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**
Drive alone for work trips (1=yes)	-0.344	-1.08	**34.1%**	-11.2%	-24.6%
Annual VMT	-4.91E-05	-1.56	20.1%	-2.7%	-17.7%
Distance from workplace (miles)	-0.105	-2.24	27.3%	-6.3%	-22.4%
Age (years)	-0.016	-1.17	**42.8%**	-13.7%	**-32.2%**
Education level (1=bachelor's degree holder)	0.841	1.87	**-32.3%**	-3.0%	**36.4%**
Annual household income ($ per year)	2.32E-06	1.10	**-31.3%**	-8.5%	**39.7%**
Population density (per mi^2)	-2.83E-04	-1.74	23.7%	-10.4%	-17.3%
Service employment density (per mi^2)	3.15E-05	1.63	-18.6%	-2.4%	22.7%
Thresholds	**Coef.**	**Std. Dev.**			
Do not support **vs.** Neutral	-0.054	0.655	--	--	--
Neutral **vs.** Support	1.270	0.251	--	--	--
Covariates (Toll if Distribute Revenues)	**Coef.**	**Z-stat**	**ΔPr_1**	**ΔPr_2**	**ΔPr_3**
Drive alone for work trips (1=yes)	-0.559	-1.83	**31.9%**	-27.1%	**-39.6%**
Distance from downtown (miles)	-0.055	-1.54	19.6%	-14.4%	-23.4%
U.S. driver license (1=yes)	-1.199	-1.48	14.3%	-13.3%	-15.5%
Age	-0.015	-1.22	**32.6%**	-23.5%	**-42.9%**
Education level (1=bachelor's degree holder)	0.872	2.12	-25.1%	8.3%	**46.9%**
Annual household income ($ per year)	3.09E-06	1.47	-26.6%	19.7%	**34.7%**
Area type (1=urban)	-0.877	-1.77	16.1%	-12.4%	-19.7%
Basic employment density (per mi^2)	4.38E-04	2.30	-13.2%	9.9%	20.3%
Thresholds	**Coef.**	**Std. Dev.**			
Do not support **vs.** Neutral	-1.667	0.415	--	--	--
Neutral **vs.** Support	-0.125	0.517	--	--	--
Correlation coefficient: 0.736 **McFadden's R-Square:** 0.075 **McFadden's adjusted R-Square:** 0.042					

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

Additionally, respondents who travel more, and live farther from their workplace in high population and service employment density neighborhoods, ceteris airbus, are likely to show refusal for tolling policy 1. Although the additional attributes (e.g., licensed drivers living farther from downtown) affecting an individual's decision regarding tolling policy 2 are different, they represent the same notion that those who travel more (probably through congested highways), all other attributes remaining equal, were likely to show refusal for both tolling policies. A high value (0.736) correlation coefficient ensures the feasibility of using seemingly unrelated bivariate OP specification here.

Chapter 22: Conclusions

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

This study also estimated how respondent demographics, built-environment factors, and travel characteristics, impact their opinions about the benefits and concerns for, and adoption of CAVs. For example, regression-model based WTP estimates, SAV adoption rates (under different pricing scenarios), and AV adoption timing collectively suggest that high-income tech-savvy[64] males, living in urban areas and having greater crash experience have more interest in and a higher WTP for these new technologies, with less dependence on friends' adoption rates[65]. Perhaps such individuals are more able

[64] 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.

[65] 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.

to appreciate and evaluate the safety benefits of smart technologies. Surveyed individuals also display a higher inclination to ultimately move closer to central Austin, possibly to enjoy the high-density of low-cost shared fleets (SAVs). In contrast, older licensed drivers expressed less interest in such technologies. They may concerned about having to learn how to use CAVs and SAVs, and licensed drivers may not be interested in losing the pleasure of driving entirely.

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

As suggested by this work, individuals foresee substantial benefits of CAVs, but also perceive hurdles. If such hurdles, or potential barriers, are not understood and managed thoughtfully, they can slow AV adoption rates to socially sub-optimal levels. Armed with such information, public agencies can craft specific policies. For example, they may create opportunities for citizens to "observe" and then "try" CVs, AVs, and

CAVs, in experience and better evaluate the "relative advantages" of such technologies. Such experiences are essential ingredients for widespread and rapid technology diffusion (Rogers 2003).Anticipating sizable profit implications, businesses also an interests in creating (and, in some cases, slowing) such opportunities. Key demographic factors and built-environment settings identified here can help businesses and public agencies to target groups with lower expected WTP values, for large-scale, real-world pilots and thoughtful design of more successful public-private partnerships.

Appendix A

```
%MATLAB Program to forecaste American's adoption rates under WTP, tech-price reduction and regulation scenario using a new simulation bsed framework:
clc
clear
[input,header]=xlsread('US.xlsx');
%input=input(1:3,:); % for test
[techinput,techheader]=xlsread('Tech_price_10_Per.xlsx');
techprice=techinput(2:15,:);
techprice(3,:)=0;
techprice(1,5:31)=0;
techprice_used=techprice;
% Level, Level2, and self-parking valet are four time costlier when added
% to a used vehicle (than added to a new vehicle)
techprice_used(2:12,:)=techprice(2:12,:)*4;
[respon,~]=size(input);
Time=31; % in years

%Households WTP for all iterations
WTPbase=zeros(respon,15);

WTPbase(:,1)=input(:,46); % connectivity
WTPbase(:,2)=input(:,47); % self-parking

for j=3:12
   for i=1:respon
      if input(i,48+(j-3)*3)==1
         WTPbase(i,j) = techprice(j,1);
      else
         WTPbase(i,j)=input(i,49+(j-3)*3); % ESC LANE_CENTER LEFT_TURN CROSS_TRAFFIC HEADLAMP PED_DET CRUISE BLIND_SPOT TRAFFIC_SIGN BRAKING
      end
   end
end

for i=1:respon
   a=rand();
   if input(i,38)>= 0
      WTPbase(i,15)=input(i,38); % Level 2
   elseif input(i,41)>=0
      WTPbase(i,15)=input(i,41);
   end
   temp1=[input(i,39),input(i,42),input(i,44)];
```

```
    WTPbase(i,14)=max(temp1); % Level 3
    temp2=[input(i,40),input(i,43),input(i,45)];
    WTPbase(i,13)=max(temp2); % Level 4
end

category=xlsread('categories.xlsx');
HHSIZEOVR3IND= input(:,22);
NUMWORKER=input(:,92);
NUMVEHOWNED=input(:,27);

for j=1:respon
    if NUMWORKER(j)>3
        NUMWORKER(j)=3;
    end
    if NUMVEHOWNED(j)>4
        NUMVEHOWNED(j)=4;
    end
end

sample=[HHSIZEOVR3IND NUMWORKER NUMVEHOWNED];
ind_sample=zeros(respon,1);
for i=1:respon
    ind_sample(i,1) = find(ismember(category, sample(i,:),'rows'));
end

[samplefreq(:,1),cat(:,1)]=hist(ind_sample,unique(ind_sample));
lencat=length(cat);
for j=1:15
    for i=1:lencat
        temp1=find(ind_sample==cat(i));
        temp2=WTPbase(temp1,j);
        temp3=temp2(temp2>0);
        if isempty(temp3)==1
            temp2=WTPbase(:,j);
            temp3=temp2(temp2>0);
        end
        for k=1:length(temp1)
            if WTPbase(temp1(k),j)==0
                WTPbase(temp1(k),j)= prctile(temp3,10) ;
            end
        end
    end
end
```

```
WTP=zeros(Time,respon,15);
for i=1:Time
   if i==1
      WTP(i,:,:)= WTPbase;
   else
      WTP(i,:,:)=WTP(i-1,:,:)*1;
   end
end

% Household priority for each level 2 technology (not interested = 1, slightly interested=2, and very interested = 3)
LEVEL2INT(:,1)=3*ones(respon,1); % ESC
LEVEL2INT(:,2)=input(:,53); % LANE_CENTER
LEVEL2INT(:,3)=input(:,56); % LEFT_TURN
LEVEL2INT(:,4)=input(:,59); % CROSS_TRAFFIC
LEVEL2INT(:,5)=input(:,62); % HEADLAMP
LEVEL2INT(:,6)=input(:,65); % PED_DET
LEVEL2INT(:,7)=input(:,68); % CRUISE
LEVEL2INT(:,8)=input(:,71); % BLIND_SPOT
LEVEL2INT(:,9)=input(:,74); % TRAFFIC_SIGN
LEVEL2INT(:,10)=input(:,77); % BRAKING

BACHLEOR_DEGREE_IND = input(:,18);
DIST_DOWNTOWN_5MILE_IND = input(:,19);
DRV_ALONE_WORK_IND= input(:,20);
FULLTIME_WORKER_IND= input(:,21);
HHSIZE_OVR3_IND= input(:,22);
JOBDEN= input(:,25);
MALE_IND= input(:,26);
PER_BELOW_POVERTY= input(:,30);
POPDEN= input(:,31);
RETIRED_IND= input(:,32);
SINGLE_IND= input(:,33);
WORKER_OVER1_IND= input(:,34);
DISABILE_IND= input(:,90);
HHINCOME= input(:,91);
NUM_WORKER= input(:,92);
US_LIC_IND= input(:,94);
VMT_OVR_9K_IND= input(:,95);
DIST_TRANSITSTOP_4MILE_IND= input(:,96);

% update after each year
AGE=zeros(respon,Time);
IND_AGE_OLDEST_VEH=zeros(respon,Time);
IND_AVG_VEH_HOLD_TIME=zeros(respon,Time);
NUM_VEH_OWNED=zeros(respon,Time);
```

```
NUM_VEH_SOLD=zeros(respon,Time);% number of vehicles sold in the past 10 years
TOT_VEH_SOLD=zeros(respon,Time); % total number of vehicles sold in the past
SOLD_VEH_IND=zeros(respon,Time);

OWNED_VEH_IND=zeros(respon,Time);
TRANSACTION=zeros(respon,Time);
AGE(:,1)= input(:,17);
IND_AGE_OLDEST_VEH(:,1)= input(:,23);
IND_AVG_VEH_HOLD_TIME(:,1)= input(:,24);
NUM_VEH_OWNED(:,1)= input(:,27);
NUM_VEH_SOLD(:,1)= input(:,28);
TOT_VEH_SOLD(:,1)=NUM_VEH_SOLD(:,1);
OWNED_VEH_IND(:,1)= input(:,29);
TRANSACTION(:,1)= input(:,35);
SOLD_VEH_IND(:,1)=input(:,93);

% 4d array (Time,Household,vehicle,attributes) for current vehicles
for j=1:respon
  j
  if NUM_VEH_OWNED(j,1) > 0
    for k=1:NUM_VEH_OWNED(j,1)
      hhcurrveh(1,j,k,1)=input(j,4+k); % manufacture year
      hhcurrveh(1,j,k,2)=input(j,10+k); % acquisition year
      if(hhcurrveh(1,j,k,2)-hhcurrveh(1,j,k,1)>0)
        hhcurrveh(1,j,k,3)=0; % new (indicator)
      else
        hhcurrveh(1,j,k,3)=1;
      end
      hhcurrveh(1,j,k,4)=0; % connectivity
      hhcurrveh(1,j,k,5)=0; % self-parking
      hhcurrveh(1,j,k,6)=input(j,48); % ESC
      hhcurrveh(1,j,k,7)=input(j,51); % LANE_CENTER
      hhcurrveh(1,j,k,8)=input(j,54); % LEFT_TURN
      hhcurrveh(1,j,k,9)=input(j,57); % CROSS_TRAFFIC
      hhcurrveh(1,j,k,10)=input(j,60); % HEADLAMP
      hhcurrveh(1,j,k,11)=input(j,63); % PED_DET
      hhcurrveh(1,j,k,12)=input(j,66); % CRUISE
      hhcurrveh(1,j,k,13)=input(j,69); % BLIND_SPOT
      hhcurrveh(1,j,k,14)=input(j,72); % TRAFFIC_SIGN
      hhcurrveh(1,j,k,15)=input(j,75); % BRAKING
      hhcurrveh(1,j,k,16)=0; % Level 4
      hhcurrveh(1,j,k,17)=0; % Level 3
    end
  else
    hhcurrveh(i,j,k,:)=zeros(17,1);
```

```
    end
end
% 4d array (Time,Household,vehicle,attributes) for sold vehicles
for j=1:respon
    j
    if NUM_VEH_SOLD(j,1) > 0
        for k=1:NUM_VEH_SOLD(j,1)
            hhsoldveh(1,j,k,1)=input(j,77+k); % sell year
            hhsoldveh(1,j,k,2)=input(j,83+k); % acquisition year
            if(hhsoldveh(1,j,k,2)-hhsoldveh(1,j,k,1)>0)
                hhsoldveh(1,j,k,3)=0; % new (indicator)
            else
                hhsoldveh(1,j,k,3)=1;
            end
            hhsoldveh(1,j,k,4)=0; % connectivity
            hhsoldveh(1,j,k,5)=0; % self-parking
            hhsoldveh(1,j,k,6)=0; % ESC
            hhsoldveh(1,j,k,7)=0; % LANE_CENTER
            hhsoldveh(1,j,k,8)=0; % LEFT_TURN
            hhsoldveh(1,j,k,9)=0; % CROSS_TRAFFIC
            hhsoldveh(1,j,k,10)=0; % HEADLAMP
            hhsoldveh(1,j,k,11)=0; % PED_DET
            hhsoldveh(1,j,k,12)=0; % CRUISE
            hhsoldveh(1,j,k,13)=0; % BLIND_SPOT
            hhsoldveh(1,j,k,14)=0; % TRAFFIC_SIGN
            hhsoldveh(1,j,k,15)=0; % BRAKING
            hhsoldveh(1,j,k,16)=0; % Level 4
            hhsoldveh(1,j,k,17)=0; % Level 3
        end
    else
        hhsoldveh(1,j,k,:)=zeros(17,1);
    end
end

% obtain a 2-d slice from a 4-d array for current vehicle
data4dcurr=hhcurrveh(1,1,:,:);
n=size(data4dcurr);
data2dcurr=zeros(n(3),n(4));
for i=1:n(3)
    for j=1:n(4)
        data2dcurr(i,j)=data4dcurr(1,1,i,j);
    end
end
% obtain a 2-d slice from a 4-d array for sold vehicle
data4dsold=hhsoldveh(1,1,:,:);
```

```
n=size(data4dsold);
data2dsold=zeros(n(3),n(4));
for i=1:n(3)
    for j=1:n(4)
        data2dsold(i,j)=data4dsold(1,1,i,j);
    end
end

%Transaction decision MNL model specification
asc1 = 0;
asc2 = -1.81;
asc3 = 0.572;
asc4 = 0;
asc5 = 0;
beta1_AGE = -0.0675;
beta1_DIST_DOWNTOWN_5MILE_IND = -0.502;
beta1_MALE_IND = 0.686;
beta1_NUM_VEH_OWNED = 0.626;
beta1_PER_BELOW_POVERTY = -0.0203;
beta1_SINGLE_IND = -0.884;
beta1_WORKER_OVER1_IND = -0.833;
beta2_AGE = -0.027;
beta2_BACHLEOR_DEGREE_IND = 0.556;
beta2_DRV_ALONE_WORK_IND = 0.415;
beta2_FULLTIME_WORKER_IND = 0.175;
beta2_MALE_IND = 0.154;
beta2_NUM_VEH_OWNED = 0.127;
beta2_OWNED_VEH_IND = 1.44;
beta2_RETIRED_IND = 0.477;
beta2_WORKER_OVER1_IND = 0.31;
beta3_AGE = -0.039;
beta3_DRV_ALONE_WORK_IND = 0.172;
beta3_HHSIZE_OVR3_IND = 0.498;
beta3_IND_AGE_OLDEST_VEH = 0.0159;
beta3_NUM_VEH_OWNED = -0.283;
beta3_PER_BELOW_POVERTY = 0.0154;
beta3_RETIRED_IND = 0.265;
beta3_SINGLE_IND = -0.146;
beta3_WORKER_OVER1_IND = 0.171;
beta4_AGE = -0.0406;
beta4_BACHLEOR_DEGREE_IND = 0.382;
beta4_DRV_ALONE_WORK_IND = 0.438;
beta4_IND_AGE_OLDEST_VEH = -0.0328;
beta4_JOBDEN = 0.0000154;
beta4_RETIRED_IND = 0.625;
```

```
%Binary logit model estimates for bought new?
alpha_NUM_VEH_OWNED = 0.4180006;
alpha_OWNED_VEH_IND = 2.304427;
alpha_IND_AGE_OLDEST_VEH = -0.093587;
alpha_NUM_VEH_SOLD = 0.535903;
alpha_SOLD_VEH_IND = -2.16244;
alpha_DISABILE_IND = -0.6397736;
alpha_NUM_WORKER = -0.4627886;
alpha_AGE = 0.0112427;
alpha_MALE_IND = 0.3497135;
alpha_US_LIC_IND = 0.7740377;
alpha_HHINCOME = 0.0000145;
alpha_FULLTIME_WORKER_IND = 0.7087637;
alpha_POPDEN = -0.0000341;
alpha_JOBDEN = 0.0000441;
alpha_CONS = -2.584207;

%Binary logit model estimates for bought two?
gama_NUM_VEH_SOLD = 0.4119785;
gama_DIST_TRANSITSTOP_4MILE_IND = 0.5270001;
gama_DIST_DOWNTOWN_5MILE_IND = -0.3238793;
gama_VMT_OVR_9K_IND = -0.5523859;
gama_DISABILE_IND = 0.6695761;
gama_NUM_WORKER = 0.3346895;
gama_MALE_IND = 0.4601743;
gama_POPDEN = 0.0000262;
gama_PER_BELOW_POVERTY = -0.0206009;
gama_SINGLE_IND = -0.7436832;
gama_CONS = -3.018543;


for i=1:Time
   utility_bought_new = alpha_CONS + alpha_NUM_VEH_OWNED * NUM_VEH_OWNED(:,i) + alpha_OWNED_VEH_IND *
OWNED_VEH_IND(:,i) + alpha_IND_AGE_OLDEST_VEH * IND_AGE_OLDEST_VEH(:,i) + alpha_NUM_VEH_SOLD *
NUM_VEH_SOLD(:,i) + alpha_SOLD_VEH_IND * SOLD_VEH_IND(:,i) + alpha_DISABILE_IND * DISABILE_IND +
alpha_NUM_WORKER * NUM_WORKER + alpha_AGE * AGE(:,i) + alpha_MALE_IND * MALE_IND + alpha_US_LIC_IND *
US_LIC_IND + alpha_HHINCOME * HHINCOME + alpha_FULLTIME_WORKER_IND * FULLTIME_WORKER_IND + alpha_POPDEN *
POPDEN + alpha_JOBDEN * JOBDEN;
   utility_bought_two = gama_CONS + gama_NUM_VEH_SOLD * NUM_VEH_SOLD(:,i) + gama_DIST_TRANSITSTOP_4MILE_IND *
DIST_TRANSITSTOP_4MILE_IND + gama_DIST_DOWNTOWN_5MILE_IND * DIST_DOWNTOWN_5MILE_IND +
gama_VMT_OVR_9K_IND * VMT_OVR_9K_IND + gama_DISABILE_IND * DISABILE_IND + gama_NUM_WORKER *
NUM_WORKER + gama_MALE_IND * MALE_IND + gama_POPDEN * POPDEN + gama_PER_BELOW_POVERTY *
PER_BELOW_POVERTY + gama_SINGLE_IND * SINGLE_IND;
   prob_bought_new = exp(utility_bought_new)./(ones(respon,1)+exp(utility_bought_new));
```

```
    prob_bought_two = exp(utility_bought_two)./(ones(respon,1)+exp(utility_bought_two));

    if (i == 1)
        for j=1:respon
            if ((TRANSACTION(j,1)==1) || (TRANSACTION(j,1)==2) ||(TRANSACTION(j,1)==4)) && (OWNED_VEH_IND(j,1)~= 1)
                TRANSACTION(j,1)=5;
            end
        end
    else
        % utility equations
        utility_SELL =    asc1 + beta1_NUM_VEH_OWNED * NUM_VEH_OWNED(:,i) + beta1_AGE * AGE(:,i) +
beta1_PER_BELOW_POVERTY * PER_BELOW_POVERTY + beta1_WORKER_OVER1_IND * WORKER_OVER1_IND +
beta1_MALE_IND * MALE_IND + beta1_SINGLE_IND * SINGLE_IND + beta1_DIST_DOWNTOWN_5MILE_IND *
DIST_DOWNTOWN_5MILE_IND;
        utility_REPLACE = asc2 + beta2_NUM_VEH_OWNED * NUM_VEH_OWNED(:,i) + beta2_OWNED_VEH_IND *
OWNED_VEH_IND(:,i) + beta2_AGE * AGE(:,i) + beta2_WORKER_OVER1_IND * WORKER_OVER1_IND + beta2_MALE_IND *
MALE_IND + beta2_RETIRED_IND * RETIRED_IND + beta2_DRV_ALONE_WORK_IND * DRV_ALONE_WORK_IND +
beta2_BACHLEOR_DEGREE_IND * BACHLEOR_DEGREE_IND + beta2_FULLTIME_WORKER_IND * FULLTIME_WORKER_IND;
        utility_BUY = asc3 + beta3_NUM_VEH_OWNED * NUM_VEH_OWNED(:,i) + beta3_IND_AGE_OLDEST_VEH *
IND_AGE_OLDEST_VEH(:,i) + beta3_AGE * AGE(:,i) + beta3_PER_BELOW_POVERTY * PER_BELOW_POVERTY +
beta3_HHSIZE_OVR3_IND * HHSIZE_OVR3_IND + beta3_WORKER_OVER1_IND * WORKER_OVER1_IND + beta3_RETIRED_IND *
RETIRED_IND + beta3_SINGLE_IND * SINGLE_IND + beta3_DRV_ALONE_WORK_IND * DRV_ALONE_WORK_IND;
        utility_ADDTECH = asc4 + beta4_IND_AGE_OLDEST_VEH * IND_AGE_OLDEST_VEH(:,i) + beta4_AGE * AGE(:,i) +
beta4_JOBDEN * JOBDEN + beta4_RETIRED_IND * RETIRED_IND + beta4_DRV_ALONE_WORK_IND * DRV_ALONE_WORK_IND +
beta4_BACHLEOR_DEGREE_IND * BACHLEOR_DEGREE_IND;
        utility_DONOTHING = asc5;

        SUM=exp(utility_SELL )+exp(utility_REPLACE)+exp(utility_BUY)+exp(utility_ADDTECH )+exp(utility_DONOTHING);
        share_SELL = exp(utility_SELL )./SUM;
        share_SELL_REPLACE = (exp(utility_SELL ) + exp(utility_REPLACE))./SUM;
        share_SELL_REPLACE_BUY = (exp(utility_SELL ) + exp(utility_REPLACE) + exp(utility_BUY))./SUM;
        share_SELL_REPLACE_BUY_ADDTECH = (exp(utility_SELL ) + exp(utility_REPLACE) + exp(utility_BUY) +
exp(utility_ADDTECH))./SUM;



        for j=1:respon
            display=[i j]
            a=rand();
            if (a <= share_SELL(j)) && (OWNED_VEH_IND(j,i)==1)
                TRANSACTION(j,i)=1;
            elseif (a > share_SELL(j)) && (a <= share_SELL_REPLACE(j)) && (OWNED_VEH_IND(j,i)==1)
                TRANSACTION(j,i)=2;
            elseif (a > share_SELL_REPLACE(j)) && (a <= share_SELL_REPLACE_BUY(j))
                TRANSACTION(j,i)=3;
```

```
        elseif (a > share_SELL_REPLACE_BUY(j)) && (a <= share_SELL_REPLACE_BUY_ADDTECH(j)) &&
(OWNED_VEH_IND(j,i)==1)
            TRANSACTION(j,i)=4;
        else
            TRANSACTION(j,i)=5;
        end
      end
   end


   for j=1:respon
      if IND_AGE_OLDEST_VEH(j,i)> 20 && (NUM_VEH_OWNED(j,i)> 0)
         TRANSACTION(j,i)=1;
         if (NUM_VEH_OWNED(j,i)-1)==0
            TRANSACTION(j,i)=2;
         end
      end
      if AGE(j,i)<71
         AGE(j,i+1)= AGE(j,i)+1;
      end
      if TRANSACTION(j,i) == 5
         hhcurrveh(i+1,j,:,:)=hhcurrveh(i,j,:,:);
         hhsoldveh(i+1,j,:,:)=hhsoldveh(i,j,:,:);
         IND_AGE_OLDEST_VEH(j,i+1)=IND_AGE_OLDEST_VEH(j,i)+1;
         IND_AVG_VEH_HOLD_TIME(j,i+1)=IND_AVG_VEH_HOLD_TIME(j,i);
         NUM_VEH_OWNED(j,i+1)=NUM_VEH_OWNED(j,i);
         TOT_VEH_SOLD(j,i+1)= TOT_VEH_SOLD(j,i);
         OWNED_VEH_IND(j,i+1)= OWNED_VEH_IND(j,i);
         NUM_VEH_SOLD(j,i+1) =length(find(hhsoldveh(i+1,j,:,1)>=2014+i-10));
         if NUM_VEH_SOLD(j,i+1)>0
            SOLD_VEH_IND(j,i+1)=1;
         else
            SOLD_VEH_IND(j,i+1)=0;
         end

      elseif TRANSACTION(j,i) == 1
         TOT_VEH_SOLD(j,i+1)= TOT_VEH_SOLD(j,i)+1;
         NUM_VEH_OWNED(j,i+1)= NUM_VEH_OWNED(j,i)-1;
         if NUM_VEH_OWNED(j,i+1)>0
            OWNED_VEH_IND(j,i+1)=1;
         end
         veh_ind = find(hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),1)==min(hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),1)));  % index of the oldest
vehicle (disposing)
         hhsoldveh(i+1,j,1:TOT_VEH_SOLD(j,i),:)=hhsoldveh(i,j,1:TOT_VEH_SOLD(j,i),:);
         hhsoldveh(i+1,j,TOT_VEH_SOLD(j,i+1),:)=hhcurrveh(i,j,veh_ind(1),:);
```

```
  hhsoldveh(i+1,j,TOT_VEH_SOLD(j,i+1),1)=2014+i; % updating selling year of sold vehicle and adding it to sold vehicles
  if veh_ind(1) <  NUM_VEH_OWNED(j,i)  % updating current vehicle inventory
    hhcurrveh(i+1,j,1:(veh_ind(1)-1),:)= hhcurrveh(i,j,1:(veh_ind(1)-1),:);
    hhcurrveh(i+1,j,veh_ind(1):NUM_VEH_OWNED(j,i+1),:)= hhcurrveh(i,j,(veh_ind(1)+1):NUM_VEH_OWNED(j,i),:);
  elseif NUM_VEH_OWNED(j,i)==1
    hhcurrveh(i+1,j,1,:)= zeros(17,1);
  else
    hhcurrveh(i+1,j,1:(veh_ind(1)-1),:)= hhcurrveh(i,j,1:(veh_ind(1)-1),:);
  end
  if NUM_VEH_OWNED(j,i+1)==0 % updaing age of the oldest vehicle
    IND_AGE_OLDEST_VEH(j,i+1)=0;
  else
    IND_AGE_OLDEST_VEH(j,i+1)=2015+i-min(hhcurrveh(i+1,j,1:NUM_VEH_OWNED(j,i+1),1));
  end

  IND_AVG_VEH_HOLD_TIME(j,i+1)=sum(hhsoldveh(i+1,j,:,1)-hhsoldveh(i+1,j,:,2))/TOT_VEH_SOLD(j,i+1);
  NUM_VEH_SOLD(j,i+1) =length(find(hhsoldveh(i+1,j,:,1)>=2014+i-10));
  if NUM_VEH_SOLD(j,i+1)>0
    SOLD_VEH_IND(j,i+1)=1;
  else
    SOLD_VEH_IND(j,i+1)=0;
  end


elseif TRANSACTION(j,i) == 3
  TOT_VEH_SOLD(j,i+1)= TOT_VEH_SOLD(j,i);
  hhsoldveh(i+1,j,:,:)=hhsoldveh(i,j,:,:);
  NUM_VEH_SOLD(j,i+1) =length(find(hhsoldveh(i+1,j,:,1)>=2014+i-10));
  if NUM_VEH_SOLD(j,i+1)>0
    SOLD_VEH_IND(j,i+1)=1;
  else
    SOLD_VEH_IND(j,i+1)=0;
  end
  IND_AVG_VEH_HOLD_TIME(j,i+1)=IND_AVG_VEH_HOLD_TIME(j,i);
  OWNED_VEH_IND(j,i+1)=1;
  hhcurrveh(i+1,j,1:NUM_VEH_OWNED(j,i),:)= hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),:);
  if(rand()< prob_bought_two(j))
    NUM_VEH_OWNED(j,i+1)= NUM_VEH_OWNED(j,i)+2;
    for m=1:2
      b=rand();
      if b < prob_bought_new(j) % probability of buying new vehicle
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,3)=1; % update buy new/used
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,2)=2014+i;% update year of acquisition
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,1)=2014+i;% update year of manufacture
        if (WTP(i,j,13))>=techprice(13,i) % Level 4
```

```
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,16)=1;
              elseif (WTP(i,j,14))>=techprice(14,i) % Level 3
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,17)=1;
              end
              if(WTP(i,j,1))>=techprice(1,i) % adding connectivity
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,4)=1;
              end
              if ( hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,16)~=1 && hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,17)~=1) % if level 3
and level 4 are not in the vehicle, then only add level 2 techs

                if WTP(i,j,2)>=techprice(2,i)
                  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5)=1;
                end

                interest=LEVEL2INT(j,:); % Level 2
                strong_interest_ind=find(interest==3);
                slight_interest_ind=find(interest==2);
                no_interest_ind=find(interest==1);
                WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
                if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
                  for p=1:length(strong_interest_ind)
                    if (WTP(i,j,2+strong_interest_ind(p)))>=techprice(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+strong_interest_ind(p),i))
                      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5+strong_interest_ind(p))=1;
                      WTPlevel2=WTPlevel2-techprice(2+strong_interest_ind(p),i);
                    end
                  end
                elseif isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
                  for p=1:length(slight_interest_ind)
                    if (WTP(i,j,2+slight_interest_ind(p)))>=techprice(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+slight_interest_ind(p),i))
                      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5+slight_interest_ind(p))=1;
                      WTPlevel2=WTPlevel2-techprice(2+slight_interest_ind(p),i);
                    end
                  end
                elseif isempty(no_interest_ind) == 0 && WTPlevel2 > 0
                  for p=1:length(no_interest_ind)
                    if (WTP(i,j,2+no_interest_ind(p)))>=techprice(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+no_interest_ind(p),i))
                      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5+ no_interest_ind(p))=1;
                      WTPlevel2=WTPlevel2-techprice(2+no_interest_ind(p),i);
                    end
                  end
                end
              end
```

```
        else
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,3)=0;
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,2)=2014+i;
            %People buy on average 6.18 year old vehicle and standard deviation is 5.48 years (given they buy old vehicle).
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,1)=round(2014+i-6.18+ (-1+2*rand())*5.48);

            if(WTP(i,j,1))>=techprice_used(1,i) % adding connectivity
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,4)=1;
            end
            if WTP(i,j,2)>=techprice_used(2,i)
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5)=1;
            end

            interest=LEVEL2INT(j,:); % Level 2
            strong_interest_ind=find(interest==3);
            slight_interest_ind=find(interest==2);
            no_interest_ind=find(interest==1);
            WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
            if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(strong_interest_ind)
                    if (WTP(i,j,2+strong_interest_ind(p))>=techprice_used(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+strong_interest_ind(p),i))
                        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5+strong_interest_ind(p))=1;
                        WTPlevel2=WTPlevel2-techprice_used(2+strong_interest_ind(p),i);
                    end
                end
            elseif isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(slight_interest_ind)
                    if (WTP(i,j,2+slight_interest_ind(p))>=techprice_used(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+slight_interest_ind(p),i))
                        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5+slight_interest_ind(p))=1;
                        WTPlevel2=WTPlevel2-techprice_used(2+slight_interest_ind(p),i);
                    end
                end
            elseif isempty(no_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(no_interest_ind)
                    if (WTP(i,j,2+no_interest_ind(p))>=techprice_used(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+no_interest_ind(p),i))
                        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)+m,5+ no_interest_ind(p))=1;
                        WTPlevel2=WTPlevel2-techprice_used(2+no_interest_ind(p),i);
                    end
                end
            end
        end
```

```
        end

    else
        NUM_VEH_OWNED(j,i+1)= NUM_VEH_OWNED(j,i)+1;
        b=rand();
        if b < prob_bought_new(j) % probability of buying new vehicle
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),3)=1;
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),2)=2014+i;
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),1)=2014+i;
            if (WTP(i,j,13))>=techprice(13,i) % Level 4
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),16)=1;
            elseif (WTP(i,j,14))>=techprice(14,i) % Level 3
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),17)=1;
            end
            if(WTP(i,j,1))>=techprice(1,i) % adding connectivity
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),4)=1;
            end
            if hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),16)~=1 && hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),17)~=1

                if(WTP(i,j,2))>=techprice(2,i)
                    hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5)=1;
                end

                interest=LEVEL2INT(j,:); % Level 2
                strong_interest_ind=find(interest==3);
                slight_interest_ind=find(interest==2);
                no_interest_ind=find(interest==1);
                WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
                if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
                    for p=1:length(strong_interest_ind)
                        if (WTP(i,j,2+strong_interest_ind(p))>=techprice(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+strong_interest_ind(p),i))
                            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+strong_interest_ind(p))=1;
                            WTPlevel2=WTPlevel2-techprice(2+strong_interest_ind(p),i);
                        end
                    end
                end
                if isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
                    for p=1:length(slight_interest_ind)
                        if (WTP(i,j,2+slight_interest_ind(p))>=techprice(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+slight_interest_ind(p),i))
                            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+slight_interest_ind(p))=1;
                            WTPlevel2=WTPlevel2-techprice(2+slight_interest_ind(p),i);
                        end
                    end
```

```
            end
            if isempty(no_interest_ind) == 0 && WTPlevel2 > 0
               for p=1:length(no_interest_ind)
                  if (WTP(i,j,2+no_interest_ind(p))>=techprice(2+no_interest_ind(p),i)) && (WTPlevel2>=techprice(2+no_interest_ind(p),i))
                     hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+ no_interest_ind(p))=1;
                     WTPlevel2=WTPlevel2-techprice(2+no_interest_ind(p),i);
                  end
               end
            end
         end
      else
         hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),3)=0;
         hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),2)=2014+i;
         %People buy on average 6.18 year old vehicle and standard deviation is 5.48 years (given they buy old vehicle).
         hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),1)=round(2014+i-6.18+ (-1+2*rand())*5.48);

         if(WTP(i,j,1))>=techprice_used(1,i) % adding connectivity
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),4)=1;
         end

         if(WTP(i,j,2))>=techprice_used(2,i)
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5)=1;
         end

         interest=LEVEL2INT(j,:); % Level 2
         strong_interest_ind=find(interest==3);
         slight_interest_ind=find(interest==2);
         no_interest_ind=find(interest==1);
         WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
         if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
            for p=1:length(strong_interest_ind)
               if (WTP(i,j,2+strong_interest_ind(p))>=techprice_used(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+strong_interest_ind(p),i))
                  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+strong_interest_ind(p))=1;
                  WTPlevel2=WTPlevel2-techprice_used(2+strong_interest_ind(p),i);
               end
            end
         end
         if isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
            for p=1:length(slight_interest_ind)
               if (WTP(i,j,2+slight_interest_ind(p))>=techprice_used(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+slight_interest_ind(p),i))
                  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+slight_interest_ind(p))=1;
                  WTPlevel2=WTPlevel2-techprice_used(2+slight_interest_ind(p),i);
               end
```

```
                end
            end
            if isempty(no_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(no_interest_ind)
                    if (WTP(i,j,2+no_interest_ind(p))>=techprice_used(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+no_interest_ind(p),i))
                        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+ no_interest_ind(p))=1;
                        WTPlevel2=WTPlevel2-techprice_used(2+no_interest_ind(p),i);
                    end
                end
            end
        end
    end
    IND_AGE_OLDEST_VEH(j,i+1)=2015+i-min(hhcurrveh(i+1,j,1:NUM_VEH_OWNED(j,i+1),1));

  elseif TRANSACTION(j,i) == 4
    TOT_VEH_SOLD(j,i+1)= TOT_VEH_SOLD(j,i);
    hhsoldveh(i+1,j,:,:)=hhsoldveh(i,j,:,:);
    NUM_VEH_SOLD(j,i+1) =length(find(hhsoldveh(i+1,j,:,1)>=2014+i-10));
    if NUM_VEH_SOLD(j,i+1)>0
        SOLD_VEH_IND(j,i+1)=1;
    else
        SOLD_VEH_IND(j,i+1)=0;
    end
    IND_AVG_VEH_HOLD_TIME(j,i+1)=IND_AVG_VEH_HOLD_TIME(j,i);

    hhcurrveh(i+1,j,:,:)=hhcurrveh(i,j,:,:);
    NUM_VEH_OWNED(j,i+1)=NUM_VEH_OWNED(j,i);
    OWNED_VEH_IND(j,i+1)= OWNED_VEH_IND(j,i);
    IND_AGE_OLDEST_VEH(j,i+1)=2015+i-min(hhcurrveh(i+1,j,1:NUM_VEH_OWNED(j,i+1),1));
    for m=1:NUM_VEH_OWNED(j,i+1)
        if(WTP(i,j,1))>=techprice_used(1,i) % adding connectivity
            hhcurrveh(i+1,j,m,4)=1;
        end

        if hhcurrveh(i+1,j,m,16)~=1 && hhcurrveh(i+1,j,m,17)~=1
            if(WTP(i,j,2))>=techprice_used(2,i) % adding self-parking
                hhcurrveh(i+1,j,m,5)=1;
            end
            ind_no_tech=find(hhcurrveh(i+1,j,m,6:15)==0); % index of tech not present in mth vehicle
            interestnew=LEVEL2INT(j,:);
            interest=interestnew(ind_no_tech);
            strong_interest_ind_new=find(interest==3);
            strong_interest_ind=ind_no_tech(strong_interest_ind_new);
            slight_interest_ind_new=find(interest==2);
```

```
            slight_interest_ind=ind_no_tech(slight_interest_ind_new);
            no_interest_ind_new=find(interest==1);
            no_interest_ind=ind_no_tech(no_interest_ind_new);
            WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
            if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
               for p=1:length(strong_interest_ind)
                  if (WTP(i,j,2+strong_interest_ind(p))>=techprice_used(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+strong_interest_ind(p),i))
                     hhcurrveh(i+1,j,m,5+strong_interest_ind(p))=1;
                     WTPlevel2=WTPlevel2-techprice_used(2+strong_interest_ind(p),i);
                  end
               end
            end
            if isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
               for p=1:length(slight_interest_ind)
                  if (WTP(i,j,2+slight_interest_ind(p))>=techprice_used(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+slight_interest_ind(p),i))
                     hhcurrveh(i+1,j,m,5+slight_interest_ind(p))=1;
                     WTPlevel2=WTPlevel2-techprice_used(2+slight_interest_ind(p),i);
                  end
               end
            end
            if isempty(no_interest_ind) == 0 && WTPlevel2 > 0
               for p=1:length(no_interest_ind)
                  if (WTP(i,j,2+no_interest_ind(p))>=techprice_used(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+no_interest_ind(p),i))
                     hhcurrveh(i+1,j,m,5+ no_interest_ind(p))=1;
                     WTPlevel2=WTPlevel2-techprice_used(2+no_interest_ind(p),i);
                  end
               end
            end
         end
      end
   elseif TRANSACTION(j,i) == 2
      TOT_VEH_SOLD(j,i+1)= TOT_VEH_SOLD(j,i)+1;
      veh_ind = find(hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),1)==min(hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),1)));
      hhsoldveh(i+1,j,1:TOT_VEH_SOLD(j,i),:)=hhsoldveh(i,j,1:TOT_VEH_SOLD(j,i),:);
      hhsoldveh(i+1,j,TOT_VEH_SOLD(j,i+1),:)=hhcurrveh(i,j,veh_ind(1),:);
      hhsoldveh(i+1,j,TOT_VEH_SOLD(j,i+1),1)=2014+i; % updating selling year of sold vehicle and adding it to sold vehicles
      NUM_VEH_SOLD(j,i+1) =length(find(hhsoldveh(i+1,j,:,1)>=2014+i-10));
      if NUM_VEH_SOLD(j,i+1)>0
         SOLD_VEH_IND(j,i+1)=1;
      else
         SOLD_VEH_IND(j,i+1)=0;
      end
```

```
IND_AVG_VEH_HOLD_TIME(j,i+1)=sum(hhsoldveh(i+1,j,:,1)-hhsoldveh(i+1,j,:,2))/TOT_VEH_SOLD(j,i+1);
OWNED_VEH_IND(j,i+1)= OWNED_VEH_IND(j,i);
if veh_ind(1) <  NUM_VEH_OWNED(j,i)  % updating current vehicle inventory
  hhcurrveh(i+1,j,1:(veh_ind(1)-1),:)= hhcurrveh(i,j,1:(veh_ind(1)-1),:);
  hhcurrveh(i+1,j,veh_ind(1):(NUM_VEH_OWNED(j,i)-1),:)= hhcurrveh(i,j,(veh_ind(1)+1):NUM_VEH_OWNED(j,i),:);
elseif NUM_VEH_OWNED(j,i)==1
  hhcurrveh(i+1,j,1,:)= zeros(17,1);
else
  hhcurrveh(i+1,j,1:(veh_ind(1)-1),:)= hhcurrveh(i,j,1:(veh_ind(1)-1),:);
end
if(rand()<prob_bought_two(j))   %Probability of buying 2 vehicles (given that HH buy a vehicle)
  NUM_VEH_OWNED(j,i+1)= NUM_VEH_OWNED(j,i)-1+2;
  for m=1:2
    b=rand();
    if b < prob_bought_new(j) % probability of buying new vehicle
      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,3)=1; % update buy new/used
      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,2)=2014+i;% update year of acquisition
      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,1)=2014+i;% update year of manufacture
      if (WTP(i,j,13))>=techprice(13,i) % Level 4
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,16)=1;
      elseif (WTP(i,j,14))>=techprice(14,i) % Level 3
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,17)=1;
      end
      if (WTP(i,j,1))>=techprice(1,i) % connectivity
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,4)=1;
      end

      if hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,16)~=1 && hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,17)~=1
        if(WTP(i,j,2))>=techprice(2,i) % adding self-parking
          hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5)=1;
        end
        interest=LEVEL2INT(j,:); % Level 2
        strong_interest_ind=find(interest==3);
        slight_interest_ind=find(interest==2);
        no_interest_ind=find(interest==1);
        WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
        if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
          for p=1:length(strong_interest_ind)
            if (WTP(i,j,2+strong_interest_ind(p)))>=techprice(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+strong_interest_ind(p),i))
              hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5+strong_interest_ind(p))=1;
              WTPlevel2=WTPlevel2-techprice(2+strong_interest_ind(p),i);
            end
          end
        elseif isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
```

```
                    for p=1:length(slight_interest_ind)
                      if (WTP(i,j,2+slight_interest_ind(p))>=techprice(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+slight_interest_ind(p),i))
                        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5+slight_interest_ind(p))=1;
                        WTPlevel2=WTPlevel2-techprice(2+slight_interest_ind(p),i);
                      end
                    end
                  elseif isempty(no_interest_ind) == 0 && WTPlevel2 > 0
                    for p=1:length(no_interest_ind)
                      if (WTP(i,j,2+no_interest_ind(p))>=techprice(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+no_interest_ind(p),i))
                        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5+ no_interest_ind(p))=1;
                        WTPlevel2=WTPlevel2-techprice(2+no_interest_ind(p),i);
                      end
                    end
                  end
                end
              else
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,3)=0;
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,2)=2014+i;
                %People buy on average 6.18 year old vehicle and standard deviation is 5.48 years (given they buy old vehicle).
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,1)=round(2014+i-6.18+ (-1+2*rand())*5.48);

                if(WTP(i,j,1))>=techprice_used(1,i) % adding connectivity
                  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,4)=1;
                end

                if(WTP(i,j,2))>=techprice_used(2,i) % adding self-parking
                  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5)=1;
                end
                interest=LEVEL2INT(j,:); % Level 2
                strong_interest_ind=find(interest==3);
                slight_interest_ind=find(interest==2);
                no_interest_ind=find(interest==1);
                WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
                if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
                  for p=1:length(strong_interest_ind)
                    if (WTP(i,j,2+strong_interest_ind(p))>=techprice_used(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+strong_interest_ind(p),i))
                      hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5+strong_interest_ind(p))=1;
                      WTPlevel2=WTPlevel2-techprice_used(2+strong_interest_ind(p),i);
                    end
                  end
                elseif isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
                  for p=1:length(slight_interest_ind)
```

```
                if (WTP(i,j,2+slight_interest_ind(p))>=techprice_used(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+slight_interest_ind(p),i))
                    hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5+slight_interest_ind(p))=1;
                    WTPlevel2=WTPlevel2-techprice_used(2+slight_interest_ind(p),i);
                end
            end
        elseif isempty(no_interest_ind) == 0 && WTPlevel2 > 0
            for p=1:length(no_interest_ind)
                if (WTP(i,j,2+no_interest_ind(p))>=techprice_used(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+no_interest_ind(p),i))
                    hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i)-1+m,5+ no_interest_ind(p))=1;
                    WTPlevel2=WTPlevel2-techprice_used(2+no_interest_ind(p),i);
                end
            end
        end
    end
end

else
    NUM_VEH_OWNED(j,i+1)= NUM_VEH_OWNED(j,i)-1+1;
    b=rand();
    if b < prob_bought_new(j) % probability of buying new vehicle
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),3)=1;
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),2)=2014+i;
        hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),1)=2014+i;
        if (WTP(i,j,13))>=techprice(13,i) % Level 4
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),16)=1;
        elseif (WTP(i,j,14))>=techprice(14,i) % Level 3
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),17)=1;
        end
        if(WTP(i,j,1))>=techprice(1,i) % adding connectivity
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),4)=1;
        end
        if  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),16)~=1 &&  hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),17)~=1
            if(WTP(i,j,2))>=techprice(2,i) % adding self-parking
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5)=1;
            end
            interest=LEVEL2INT(j,:); % Level 2
            strong_interest_ind=find(interest==3);
            slight_interest_ind=find(interest==2);
            no_interest_ind=find(interest==1);
            WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
            if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(strong_interest_ind)
                    if (WTP(i,j,2+strong_interest_ind(p))>=techprice(2+strong_interest_ind(p),i)) &&
```

```
(WTPlevel2>=techprice(2+strong_interest_ind(p),i))
                    hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+strong_interest_ind(p))=1;
                    WTPlevel2=WTPlevel2-techprice(2+strong_interest_ind(p),i);
                  end
                end
              end
              if isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(slight_interest_ind)
                  if (WTP(i,j,2+slight_interest_ind(p))>=techprice(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice(2+slight_interest_ind(p),i))
                    hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+slight_interest_ind(p))=1;
                    WTPlevel2=WTPlevel2-techprice(2+slight_interest_ind(p),i);
                  end
                end
              end
              if isempty(no_interest_ind) == 0 && WTPlevel2 > 0
                for p=1:length(no_interest_ind)
                  if (WTP(i,j,2+no_interest_ind(p))>=techprice(2+no_interest_ind(p),i)) && (WTPlevel2>=techprice(2+no_interest_ind(p),i))
                    hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+ no_interest_ind(p))=1;
                    WTPlevel2=WTPlevel2-techprice(2+no_interest_ind(p),i);
                  end
                end
              end
            end
          else
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),3)=0;
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),2)=2014+i;
            %People buy on average 6.18 year old vehicle and standard deviation is 5.48 years (given they buy old vehicle).
            hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),1)=round(2014+i-6.18+ (-1+2*rand())*5.48);

            if(WTP(i,j,1))>=techprice_used(1,i) % adding connectivity
              hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),4)=1;
            end
            if(WTP(i,j,2))>=techprice_used(2,i) % adding self-parking
              hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5)=1;
            end
            interest=LEVEL2INT(j,:); % Level 2
            strong_interest_ind=find(interest==3);
            slight_interest_ind=find(interest==2);
            no_interest_ind=find(interest==1);
            WTPlevel2=WTP(i,j,15); % willingness to pay for Level 2 vehicles
            if  isempty(strong_interest_ind) == 0 && WTPlevel2 > 0
              for p=1:length(strong_interest_ind)
                if (WTP(i,j,2+strong_interest_ind(p))>=techprice_used(2+strong_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+strong_interest_ind(p),i))
```

```
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+strong_interest_ind(p))=1;
                WTPlevel2=WTPlevel2-techprice_used(2+strong_interest_ind(p),i);
              end
            end
          end
          if isempty(slight_interest_ind) == 0 && WTPlevel2 > 0
            for p=1:length(slight_interest_ind)
              if (WTP(i,j,2+slight_interest_ind(p))>=techprice_used(2+slight_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+slight_interest_ind(p),i))
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+slight_interest_ind(p))=1;
                WTPlevel2=WTPlevel2-techprice_used(2+slight_interest_ind(p),i);
              end
            end
          end
          if isempty(no_interest_ind) == 0 && WTPlevel2 > 0
            for p=1:length(no_interest_ind)
              if (WTP(i,j,2+no_interest_ind(p))>=techprice_used(2+no_interest_ind(p),i)) &&
(WTPlevel2>=techprice_used(2+no_interest_ind(p),i))
                hhcurrveh(i+1,j,NUM_VEH_OWNED(j,i+1),5+ no_interest_ind(p))=1;
                WTPlevel2=WTPlevel2-techprice_used(2+no_interest_ind(p),i);
              end
            end
          end
        end
      end
      IND_AGE_OLDEST_VEH(j,i+1)=2015+i-min(hhcurrveh(i+1,j,1:NUM_VEH_OWNED(j,i+1),1));
    end
  end
end

%To obtain output
set=[1 6 11 16 21 26 31];
HHWEIGHT= input(:,3);
header1={'ID','MAKE_YEAR', 'ACQ_YEAR', 'BOUGHT_NEW_IND','CONNECTIVITY', 'SELF-PARKING','ESC', 'LANE_CENTER',
'LEFT_TURN', 'CROSS_TRAFFIC','HEADLAMP', 'PED_DET', 'CRUISE',  'BLIND_SPOT', 'TRAFFIC_SIGN', 'BRAKING', 'LEVEL4',
'LEVEL3'};
header2={'ID','TRANSACTION', 'NUM_VEH_OWNED', 'NUM_VEH_SOLD', 'TOT_VEH_SOLD', 'IND_AVG_VEH_HOLD_TIME',
'IND_AGE_OLDEST_VEH', 'CONNECTIVITY', 'SELF-PARKING','ESC', 'LANE_CENTER', 'LEFT_TURN',
'CROSS_TRAFFIC','HEADLAMP', 'PED_DET', 'CRUISE',  'BLIND_SPOT', 'TRAFFIC_SIGN', 'BRAKING', 'LEVEL4', 'LEVEL3'};
count_HH_with_tech=zeros(length(set),14);
count_HH_with_veh=zeros(length(set),1);

prop_veh_with_tech=zeros(length(set),14);
prop_used_veh_with_tech=zeros(length(set),14);
prop_new_veh_with_tech=zeros(length(set),14);
```

```
for k=1:length(set)
    i=set(k);
    output1=zeros(sum(NUM_VEH_OWNED(:,i)),19);
    count_veh_with_tech = zeros(1,14);
    count_new_veh_with_tech=zeros(1,14);
    count_used_veh_with_tech=zeros(1,14);
    count_new_veh=0;
    count_used_veh=0;
    for j=1:respon
        if j==1
            start=1;
        else
            start=sum(NUM_VEH_OWNED(1:j-1,i))+1;
        end
        ending=sum(NUM_VEH_OWNED(1:j,i));
        output1(start:ending,1)=j;
        output1(start:ending,2:18)=hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),:);
        output1(start:ending,19)=ones(NUM_VEH_OWNED(j,i),1)*HHWEIGHT(j);

        if NUM_VEH_OWNED(j,i)>0
            count_HH_with_veh(k,1)=count_HH_with_veh(k,1)+HHWEIGHT(j);
            for s=1:14
                if (s<=12 && s>=2)
summation=hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),3+s)+hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),16)+hhcurrveh(i,j,1:NUM_VEH_OWNE
D(j,i),17);
                    ind=find(summation>0);
                else
                    ind=find(hhcurrveh(i,j,1:NUM_VEH_OWNED(j,i),3+s)==1);
                end
                dummy=length(ind);
                if dummy > 0
                    count_HH_with_tech(k,s)=count_HH_with_tech(k,s)+HHWEIGHT(j);
                end
            end
        end
    end

    years(:,1)=set+2014;
    [len,~]=size(output1);
    total_weight=sum(output1(:,19)); % total weight for all vehicles
    for r=6:16
        for p=1:len
            summation=output1(p,r)+output1(p,17)+output1(p,18);
```

```
            if summation>0
                output1(p,r)=1;
            end
        end
    end

    for j=1:len
        if output1(j,4)==1
            count_new_veh = count_new_veh +  output1(j,19);
        else
            count_used_veh = count_used_veh +  output1(j,19);
        end
        for s=1:14

            count_veh_with_tech(1,s)=  count_veh_with_tech(1,s) + output1(j,4+s)*output1(j,19);
            if output1(j,4)==1
                count_new_veh_with_tech(1,s)=count_new_veh_with_tech(1,s) + output1(j,4+s)*output1(j,19);
            else
                count_used_veh_with_tech(1,s)=count_used_veh_with_tech(1,s) + output1(j,4+s)*output1(j,19);
            end
        end
    end
    prop_veh_with_tech(k,:) = (count_veh_with_tech/total_weight)*100;
    prop_used_veh_with_tech(k,:)=(count_used_veh_with_tech/count_used_veh)*100;
    prop_new_veh_with_tech(k,:)=(count_new_veh_with_tech/count_new_veh)*100;
end


output4_initial=bsxfun(@rdivide, count_HH_with_tech,count_HH_with_veh);
output4=[years output4_initial*100];
output5=[years (count_HH_with_tech/respon)*100];
output6 =[years  prop_veh_with_tech];
output7 =[years  prop_used_veh_with_tech];
output8 =[years  prop_new_veh_with_tech];

header4={'YEAR', 'CONNECTIVITY', 'SELF-PARKING','ESC', 'LANE_CENTER', 'LEFT_TURN', 'CROSS_TRAFFIC','HEADLAMP',
'PED_DET', 'CRUISE',  'BLIND_SPOT', 'TRAFFIC_SIGN', 'BRAKING', 'LEVEL4', 'LEVEL3'};

xlswrite('US_10per_final_technology_adoption_improved.xlsx',output5,'per_HH_tech_adoption','A2');
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xlswrite('US_10per_final_technology_adoption_improved.xlsx',output6,'per_veh_with_tech','A2');
xlswrite('US_10per_final_technology_adoption_improved.xlsx',header4,'per_veh_with_tech','A1');
```

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