Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles

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2016

Abstract

Autonomous vehicles use sensing and communication technologies to navigate safely and efficiently with little or no input from the driver. These driverless technologies will create an unprecedented revolution in how people move, and policymakers will need appropriate tools to plan for and analyze the large impacts of novel navigation systems. In this paper we derive semiparametric estimates of the willingness to pay for automation. We use data from a nationwide online panel of 1,260 individuals who answered a vehicle-purchase discrete choice experiment focused on energy efficiency and autonomous features. Several models were estimated with the choice microdata, including a conditional logit with deterministic consumer heterogeneity, a parametric random parameter logit, and a semiparametric random parameter logit. We draw three key results from our analysis. First, we find that the average household is willing to pay a significant amount for automation: about \$3,500 for partial automation and \$4,900 for full automation. Second, we estimate substantial heterogeneity in preferences for automation, where a significant share of the sample is willing to pay above \$10,000 for full automation technology while many are not willing to pay any positive amount for the technology. Third, our semiparametric random parameter logit estimates suggest that the demand for automation is split approximately evenly between high, modest and no demand, highlighting the importance of modeling flexible preferences for emerging vehicle technology.

JEL classification: C25, D12, Q42

Key words: willingness to pay, autonomous vehicle technology, discrete choice models, semiparametric heterogeneity

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1 Introduction

Personal mobility is about to experience an unprecedented revolution motivated by technological change in the automotive industry (National Highway Traffic Safety Administration, 2013; Fagnant and Kockelman, 2014). The introduction of automated vehicles –in which at least some (and potentially all) control functions occur without direct input from the driver– will completely change how people move. The adoption of automated navigation systems has the potential to dramatically reduce traffic congestion and accidents, while creating substantial improvements in the overall trip experience as well as providing enhanced accessibility opportunities to people with reduced mobility (Fagnant and Kockelman, 2015).

Automated vehicles use sensing and communication technologies to navigate safely and efficiently with little or no human input. Automated navigation technology comprises any combination of (1) self-driving navigation systems informed by on-board sensors (*autonomous* vehicles) vehicle-to-vehicle (V2V) and (2) vehicle-to-infrastructure (V2I) communication systems that inform navigation and collision avoidance applications (*connected* vehicles). The National Highway Traffic Safety Administration (NHTSA) has suggested five levels of automated navigation: level 0 (no automation), where the driver is in complete control of safety-critical functions; level 1 (function-specific automation), where the driver cedes limited control of certain functions to the vehicle especially in crash-imminent situations (adaptive cruise control, electronic stability control ESC, automatic braking); level 2 (combined-function automation), which enables hands-off-wheel and foot-off-pedal operations, but the driver is expected to be available at all times to resume control of the vehicle (adaptive cruise control and lane centering); level 3 (limited self-driving or conditional automation), where the vehicle potentially controls all safety functions under certain traffic and environmental conditions, but some conditions require transition to driver control; and level 4 (driverless or full self-driving automation), where the vehicle controls all safety functions and monitors conditions for the whole trip.[1]

[1] A six level categorization is proposed by the Society of Automotive Engineers, which further distinguishes levels within NHTSA level 4.

Imminent commercialization of automated cars is best exemplified by the recent announcement (October 2016) that all new Tesla vehicles will have full self-driving hardware.[2] Several semi-autonomous features are already available in the automotive market, mostly in the form of in-vehicle crash avoidance upgrades with preventive warnings or limited automated control of safety functions, such as braking when danger is detected. Self-parking assist systems are another example of a more advanced upgrade that is currently available in select makes and models. These entry-level automation packages are possible as a result of vehicles being equipped with radar, cameras, and other sensors. Even though technology is still evolving, full automation is possible with the current stage of development. The Google car and its more than 2 million miles of driverless driving is the most publicized effort.[3]

The literature on vehicle-to-vehicle, vehicle-to-infrastructure, and control systems for safe navigation is extensive. Regulation, insurance, and liability are other areas where there is strong debate. However, little attention has been devoted to the analysis of automated vehicles as marketable products. Consumer acceptance is critical to forecast adoption rates, especially if one considers that there may be strong barriers to entry (potential high costs, concerns that technology may fail).

Our work contributes to two strands of literature on the demand for new technology. The first area is the recent development in understanding the demand, penetration, and policy implications of autonomous vehicle technology. Several recent studies attempt to understand how consumer preferences for attributes such as safety, travel time, and performance shape the demand for driverless cars. Kyriakidis et al. (2015) conducted an international public opinion questionnaire of 5,000 respondents from 109 countries. Responses were diverse: 22 percent of the respondents did not want to pay any additional price for a fully automated navigation system, whereas 5 percent indicated they would be willing to pay more than $30,000. Payre et al. (2014) conducted a similar survey of 421 French drivers with questions eliciting the acceptance of fully automated driving. Among those surveyed, 68.1 percent accepted fully automated driving unconditionally, with higher acceptance

[2]Source: `https://www.tesla.com/blog/all-tesla-cars-being-produced-now-have-full-self-driving-hardware`

[3]Source: `https://www.google.com/selfdrivingcar/faq/`

conditional on the type of driving, including usage of highway driving, in the presence of traffic congestion, and for automated parking. Similar results were obtained in a survey of Berkeley, California, residents conducted by Howard and Dai (2013). Individuals in this survey were most attracted to the potential safety, parking, and multi-tasking benefits. Schoettle and Sivak (2014) conducted a much larger and more internationally based survey of residents from China, India, Japan, the United States, the United Kingdom, and Australia. The authors found that respondents expressed high levels of concern about riding in self-driving vehicles, with the most pressing issues involving those related to equipment or system failure. While most expressed a desire to own an autonomous vehicle, many respondents stated that they were unwilling to pay extra for the technology.

A paper related to our own is that by Bansal et al. (2016), which estimates willingness to pay for different levels of automation. They find that for their sample of 347 residents of Austin, Texas, willingness to pay (WTP) for full automation is $7,253, which is substantially higher than our own estimate. The authors also estimate WTP for partial automation of $3,300, which is similar to our estimate.

Our demand estimates contribute to the assessment of the social costs and benefits of autonomous vehicles. Fagnant and Kockelman (2015) estimate the external net benefits from autonomous vehicle penetration. They find that the social net benefits including crash savings, travel time reduction from less congestion, fuel efficiency savings, and parking benefits total between $2,000 and $4,000 per vehicle. These estimates, however, greatly depend on how the presence of autonomous vehicles will impact both vehicle ownership and utilization. For example if autonomous vehicles make owning a vehicle more desirable, then the stock and use of vehicles may increase, reducing the external net benefits.

We designed a web-based survey with a discrete choice experiment to determine early-market empirical estimates of the structural parameters that characterize current preferences for autonomous and semi-autonomous electric vehicles. The discrete choice experiment contained as experimental attributes three levels of automation: no automation, some or partial automation ("automated crash avoidance"), and full automation ("Google car"). Automation was allowed for alternative powertrains (hybrid electric, plug-in hybrid and full battery electric).

Based on the results from this experiment, we estimate WTP for automation. Our estimates of WTP for privately owned autonomous vehicles take a first step to understanding the demand for this technology, which is critical for understanding how aggregate demand for vehicles and vehicle miles traveled will respond to the technology over time.[4]

In addition to the discrete choice experiment of vehicle purchase, the survey also contained an experiment to elucidate the subjective discount rate of potential vehicle buyers. Expanding on the work of Newell and Siikamäki (2013), we used the individual-level experimental discount rate to determine the present value of fuel costs for each alternative.

To derive flexible estimates of the heterogeneity distribution of the willingness to pay for automation, we implemented the maximum simulated likelihood estimator of a logit-based model with discrete continuous heterogeneity distributions, in which the parameters (mean and standard deviation) of continuous heterogeneity distributions have associated discrete, unknown probabilities. The approach adopted to unobserved preference heterogeneity in this paper thus takes into consideration a mixed-mixed logit model (Bujosa et al., 2010; Greene and Hensher, 2013; Keane and Wasi, 2013), where the random willingness-to-pay parameters are distributed according to a Gaussian mixture. The weights of the Gaussian mixture can include individual-specific covariates that allow us to identify clusters with differing willingness to pay for automation. The estimator was implemented with analytical expressions of the score for computation efficiency.

Methodologically, we highlight the importance of allowing for flexible distributions of preferences for vehicle attributes such as automation by comparing estimates from a standard mixed logit specification with a more flexible mixed-mixed logit specification. We find richer heterogeneity estimates with the more flexible specification,

[4]We do not explore demand for autonomous commercial vehicles or for autonomous public transportation. Initial work in this area includes a study by Greenblatt and Saxena (2015) which simulates the greenhouse gas impact of autonomous vehicle taxis and finds that they can dramatically reduce greenhouse gas emissions relative to conventional taxis. A promising area of future research involves incorporating our survey and econometric methods for eliciting WTP to determine how households tradeoff cost savings, travel time, safety, and other desirable attributes with alternative travel modes with and without a human driver.

where demand for automation appears evenly split between high, modest and no demand.

The remainder of the paper is organized as follows. In section 2, we present a series of discrete choice models that we use to estimate how consumers value personal vehicle automation. In section 3, we discuss the survey data and provide summary statistics of the sample. We then present the empirical models and estimation results in section 4 and draw conclusions based on our results in section 5.

2 Structural Vehicle Choice Models

The purchase of an automated vehicle can be modeled as the consumer choice to adopt high technology, durable goods. The use of discrete choice models to analyze vehicle purchases in general dates back to the earliest econometric applications of the principle of random utility maximization. Within this literature, great interest in modeling the adoption of battery electric vehicles has emerged in the last five years (for literature reviews, see Rezvani et al., 2015; Al-Alawi and Bradley, 2013).

Because the transition to energy efficiency in personal transportation is characterized by the trade-off between higher purchase prices and lower operating costs, a specific avenue of research has been taking into account time preferences to represent how consumers discount future savings. Seminal work on the problem of estimating individual discount rates with discrete choice models includes Hausman (1979), Lave and Train (1979), and the technical reports cited in Train (1985). In addition, recent literature reviews are provided by Frederick et al. (2002) and Cameron and Gerdes (2005). Expanding on Jaffe and Stavins (1994), several resource and energy economists have added to the debate about the energy paradox (Newell and Siikamäki, 2013; Allcott and Greenstone, 2012; Ansar and Sparks, 2009; Van Soest and Bulte, 2001; DeCanio, 1998; Hassett and Metcalf, 1993). As reviewed in Wang and Daziano (2015), there are two approaches to introducing discount rates in discrete choice models: endogenous discounting, in which discount rate estimates are derived from the marginal rate of substitution between price and operating cost, and exogenous discounting, in which the discount rate is assumed as known.

Working with exogenous discount rates has been proposed in the energy economics literature to avoid confounding effects in the determination of discount rate estimates coming from market failures (Allcott and Wozny, 2014; Newell and Siikamäki, 2013). Exogenous discounting takes as known the discount rate of individual i, making it straightforward to calculate the present value of future costs of product j, PVFC_{ij}. Moving future cash flows to the present allows the researcher to use a static discrete choice specification. If in addition to monetary attributes, vehicle design attributes $\mathbf{x}_{ij}$ are considered (such as power, drivetrain, refueling time, and driving range), then the conditional indirect utility for individual i choosing alternative j can be specified as

$$U_{ij} = \mathbf{x}'_{ij}\boldsymbol{\omega}_{\mathbf{x},i} - \alpha_i \text{price}_{ij} - \gamma_{\text{PVFC},i}\text{PVFC}_{ij} + \varepsilon_{ij}. \tag{1}$$

Equation (1) represents our benchmark specification and is formulated in preference space. $\boldsymbol{\omega}_{\mathbf{x},i}$ is the change in utility from marginal improvements in the (nonmonetary) vehicle design attributes that are captured in the vector $\mathbf{x}_{ij}$, α_i is the marginal utility of income, and $\gamma_{\text{PVFC},i}$ is the change in utility from a marginal change in the present value of fuel costs. For a rational consumer $\gamma_{\text{PVFC},i} = \alpha_i$, since both price_{ij} and PVFC_{ij} are monetary attributes at the time of purchase. If $\gamma_{\text{PVFC},i} < \alpha_i$, then there is evidence for myopic consumption (as consumers weigh more than saving one dollar in purchase price than the same dollar in discounted future costs), and $\gamma_{\text{PVFC},i} > \alpha_i$ reveals that consumers overvalue fuel costs. In our benchmark specification, we assume that the idiosyncratic error term ε_{ij} is i.i.d. distributed Type 1 extreme value, so that predicted probabilities take on the conditional logit form.

In this paper, in addition to standard assumptions of unobserved heterogeneity in the parameters (such as normally and lognormally distributed parameters), we consider a semi-parametric discrete-continous mixture for the heterogeneity distributions. In fact, we adopt and implement the idea of the mixed-mixed logit model (MM-MNL) that represents heterogenous preferences as a weighted average of normals (Bujosa et al., 2010; Greene and Hensher, 2013; Keane and Wasi, 2013).[5]

If $\boldsymbol{\theta}'_i = (\alpha_i, \gamma_{\text{PVFC},i}, \boldsymbol{\omega}'_{\mathbf{x},i})$ represents the full vector of parameters of interest, the heterogeneity distribution assumption is the following Gaussian mixture with Q components: $\boldsymbol{\theta}_i \sim \mathcal{N}(\boldsymbol{\theta}_q, \boldsymbol{\Sigma}_q)$ with probability w_{iq} for $q \in \{1, \ldots, Q\}$ or $f_{\boldsymbol{\Theta}}(\boldsymbol{\theta}_i) =$

[5] Any continuous distribution can be approximated by a discrete mixture of normal distributions (Train, 2008).

$\sum_{q=1}^{Q} w_{iq} f_q(\boldsymbol{\theta}_i)$, where $f_{\boldsymbol{\Theta}}$ is the density function of the heterogeneity distribution of the parameters of interest and $f_q(\boldsymbol{\theta}_i)$ is the multivariate normal density with parameters $\boldsymbol{\theta}_q$ and $\boldsymbol{\Sigma}_q$. The weights of the mixture w_{iq} can be interpreted as class assignment probabilities, and can be constant or a function of covariates. In particular, the weights can be specified as a function $w_{iq} = w_{iq}(\mathbf{z}_i|\boldsymbol{\delta})$, where $\mathbf{z}_i$ is a vector of individual-specific characteristics and $\boldsymbol{\delta}$ is a vector of parameters. As in latent class discrete choice models, a possibility is to assume a logit-type specification for the mixture weights:

$$w_{iq} = \frac{\exp(\mathbf{z}_i' \boldsymbol{\delta}_q)}{\sum_{q=1}^{Q} \exp(\mathbf{z}_i' \boldsymbol{\delta}_q)}, \tag{2}$$

where the vector component-specific (or class-specific) parameter vector is normalized for identification. For example, normalizing $\boldsymbol{\delta}_1 = \mathbf{0}$ ensures that the parameters for the rest of the components are identified.

Assume that we observe T choices made by individual i. We denote the choice made by individual i by $y_{ijt} = 1$ if individual i chose alternative j in choice occasion t and $y_{ijt} = 0$ otherwise. Furthermore, assume that ε_{ijt} is i.i.d. type 1 extreme value for $t \in \{1, \ldots, T\}$, the MM-MNL probability of the sequence of choices is given by:

$$P_i = \sum_{q=1}^{Q} w_{iq}(\boldsymbol{\delta}) \int \left\{ \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp\left(\mathbf{x}_{ij}' \boldsymbol{\omega}_{\mathbf{x},i} - \alpha_i \text{price}_{ij} - \gamma_{\text{PVFC},i} \text{PVFC}_{ij}\right)}{\sum_{j=1}^{J} \exp\left(\mathbf{x}_{ij}' \boldsymbol{\omega}_{\mathbf{x},i} - \alpha_i \text{price}_{ij} - \gamma_{\text{PVFC},i} \text{PVFC}_{ij}\right)} \right]^{y_{ijt}} \right\} f_q(\boldsymbol{\theta}_i) d\boldsymbol{\theta}_i. \tag{3}$$

As in a mixed logit model, the above probability can be approximated using Monte Carlo integration:

$$\tilde{P}_i = \frac{1}{R} \sum_{q=1}^{Q} w_{iq}(\boldsymbol{\delta}) \sum_{r=1}^{R} \left\{ \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp\left(\mathbf{x}_{ij}' \boldsymbol{\omega}_{\mathbf{x},i,q}'^{(r)} - \alpha_{i,q}^{(r)} \text{price}_{ij} - \gamma_{\text{PVFC},i,q}^{(r)} \text{PVFC}_{ij}\right)}{\sum_{j=1}^{J} \exp\left(\mathbf{x}_{ij}' \boldsymbol{\omega}_{\mathbf{x},i,q}'^{(r)} - \alpha_{i,q}^{(r)} \text{price}_{ij} - \gamma_{\text{PVFC},i,q}^{(r)} \text{PVFC}_{ij}\right)} \right]^{y_{ijt}} \right\}, \tag{4}$$

where $(\alpha_{i,q}^{(r)}, \gamma_{\text{PVFC},i,q}^{(r)}, \boldsymbol{\omega}_{\mathbf{x},i,q}'^{(r)})$ represents random draw $r \in \{1, \ldots, R\}$ from the normal density $f_q(\boldsymbol{\theta}_i|\boldsymbol{\theta}_q,\boldsymbol{\Sigma}_q)$.

Finally, using the Monte Carlo approximation of the probability of the sequence of choices by individual i, it is possible to find the maximum simulated likelihood estimator by maximizing the following simulated likelihood:

$$\tilde{\ell}(\boldsymbol{\theta}^Q, \boldsymbol{\delta}^Q, \boldsymbol{\Sigma}^Q; \mathbf{y}|\mathbf{X}, \mathbf{Z}, \mathbf{price}, \mathbf{PVFC}) = \prod_{i=1}^{N} \tilde{P}_i, \tag{5}$$

where $\boldsymbol{\theta}^Q = (\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_Q)$, $\boldsymbol{\delta}^Q = (\boldsymbol{\delta}_2, \ldots, \boldsymbol{\delta}_Q)$ (if the first component is normalized), and $\boldsymbol{\Sigma}^Q = (\boldsymbol{\Sigma}_1, \ldots, \boldsymbol{\Sigma}_Q)$.

3 Vehicle Choice Data

3.1 The survey

To support design of the survey, we first conducted two focus groups where new vehicle preferences and attitudes toward automated cars were discussed by randomly selected potential car buyers.[6] 15 participants in Upstate New York (aged 18-62) and 12 participants in New York City (aged 18-55) discussed benefits and eventual dangers of automation. All participants had a driving license, and in the case of Upstate New York, all commuted by car daily. Only 4 of the participants in New York City drove a car daily, whereas 6 drove a car occasionally. Diverse income levels were represented, but the median household income was around $50,000 in both groups. There were 9 males in the Upstate New York group, and 8 in the New York City group.

Among the benefits, participants mentioned fewer traffic jams, increased mobility independence, and easier and quicker parking. Another benefit of automation that was discussed was the possibility of multitasking and increased productivity. One of the most relevant features that people look for in a new car is safety (Koppel et al., 2008; Daziano, 2012). Participants of the focus groups confirmed that safety is a major concern. However, their perceptions about driverless cars and safety were divided. Some participants agreed that automation has great potential to reduce accidents, but a majority also said that unfortunately systems fail. Concerns about lighter vehicles being more dangerous also were raised. The qualitative information that was collected in the focus groups was used to design an attitudinal module of the survey, which supplements the data that were collected using the discrete choice experiment.

3.2 The data

We used the Qualtrics online platform to collect the survey data. We surveyed a sample of individuals who provided valid responses for personal characteristics questions and all of the vehicle choice experiments. Qualtrics is a private market research company that offers online surveying software as well as management of

[6] Recruitment of participants was facilitated by the Cornell Survey Research Institute.

online panels of respondents that match specific requirements.[7] We collected several waves of responses among adults with a driving license between September 12, 2014, and October 2, 2014, for a total of 1,260 individuals.[8]

Table 1 reports demographic statistics for respondents in our sample. The sample is broadly representative of the U.S. population. Mean and median household incomes are \$61,226 and \$55,000, respectively, which are close to reported estimates from the 2013 American Community Survey;[9] the sample's fraction of married adults well represents the estimates of the U.S. marriage rate of around 50 percent; the unemployment rate of 5.79 percent among our sample respondents is close to the most recently reported national unemployment rate for September 2014 of 5.9 percent.[10]

The sample appears to only slightly over-represent white respondents and slightly under-represent minorities; the U.S. Census reports that 77.7 percent of U.S. citizens are white, while our sample includes 85 percent.[11] Our sample is slightly more educated relative to the average for U.S. citizens; 38 percent of respondents state that they have earned at least a bachelor's degree, while only about 30 percent of U.S. citizens have done so. These small differences can be explained by the screening process of our survey. Two screening questions, whether the respondent has a driver's license and whether the respondent has access to a household vehicle, likely disproportionately discourage minorities and less educated individuals from taking our survey. Fortunately, however, this effect appears to be quite mild as suggested by the descriptive statistics of our sample.

Table 2 reports statistics for the vehicle holdings data in our sample. These data represent vehicles that are driven most often among all vehicles held by respondent households. We merge survey responses on the model year, make, model and trim of the vehicle with trim-level characteristics data from Ward's Automotive.[12] Vehicle

[7]More information in this platform is available at https://www.qualtrics.com/

[8]Out of the sample of 1,260, 549 responses were collected between September 12 and September 15, 214 were collected between September 19 and September 23, and the remaining responses were collected between September 29 and October 2.

[9]These estimates are available at `http://www.census.gov/content/dam/Census/library/publications/2014/acs/acsbr13-02.pdf`.

[10]See `http://data.bls.gov/timeseries/LNS14000000`.

[11]See `http://quickfacts.census.gov/qfd/states/00000.html`.

[12]The Ward's Automotive data include detailed characteristics of vehicles identified by model year, make, model, series, body style, fuel type, and drive type. Data for vehicles with model years 1996-2014 were purchased from WardsAuto.com.

age and annual vehicle miles traveled (VMT) are based on two questions in our survey.

The average age among all vehicles is seven years, which is about two years younger than the average age of all autos held by households in 2008.[13] This seems reasonable considering that the reported vehicle holding in our survey is conditional on being the vehicle that is driven most often and not simply a random vehicle chosen from the full set of household vehicle holdings.[14] For the same reason, annual VMT is slightly over 15,000 miles, which is close to the average reported VMT of new cars and light trucks.[15] The selection is also a reason why the average vehicle fuel economy in our sample is remarkably high.[16] Average fuel economy of automobiles sold in 2007–the average model year of vehicles in our sample–was around 20 miles per gallon. Households in our sample, however, likely optimize their fleet utilization choices by driving their relatively fuel efficient vehicles more than their relatively fuel inefficient vehicles. Therefore, the vehicles that respondents report are more likely to have high fuel economy.

Patterns in vehicle characteristics across the different styles are in line with expectations. Fuel efficiency measured in miles per gallon is higher for smaller cars including coupés, sedans, and wagons and lower for larger, more powerful autos including trucks and SUVs. Trucks are older than the average vehicle by about three years, which is also in line with data from the 2009 National Household Transportation Survey.[17] Trucks are generally driven more per year and over the entire vehicle lifetime than cars, which is consistent with the reported travel data from our survey.[18]

[13] This is based on the 2009 National Household Transportation Survey, Summary of Travel Trends: `http://nhts.ornl.gov/2009/pub/stt.pdf`

[14] It is well documented that vehicles with more annual miles traveled are generally newer. See Lu (2006), `http://www-nrd.nhtsa.dot.gov/Pubs/809952.pdf`, for more details.

[15] Lu (2006) documents that the average VMT for new cars is 14,231, which falls to 12,325 by age seven; the average VMT for new trucks is 16,085, which falls to 12,356 by year 10. See `http://www-nrd.nhtsa.dot.gov/Pubs/809952.pdf`.

[16] In fact, it is close to the average record high 24.9 miles per gallon fuel economy of new 2013 model year vehicles. See `http://www.umich.edu/~umtriswt/EDI_sales-weighted-mpg.html`.

[17] See `http://nhts.ornl.gov/2009/pub/stt.pdf`..

[18] For more details, see Lu (2006), `http://www-nrd.nhtsa.dot.gov/Pubs/809952.pdf`.

3.3 Design of the choice experiment

The discrete choice experiment that we designed is based on a labeled experiment with quasi-customized alternative attributes. The alternatives are constructed according to general new vehicle preferences, including stated price thresholds. The experiment attributes include purchase price, fuel cost expenses, driving range, recharging time, and levels of hybridization and automation. Levels are described in Table 3. Note that purchase price in the experiment was customized to the threshold stated by the respondent (validated according to household income) when asked about the willingness to spend in buying a new vehicle.

For automation we considered an aggregation of the technology NHTSA levels in three groups: no automation (base), some automation ("automated crash avoidance"), and full automation ("Google car"). The decision to aggregate the automation levels was based on that technical attributes are not necessarily the same as consumer-level attributes, that two markets aggregating the automated levels into semi- and full automation have already been identified (Grush et al., 2016), and that participants in the two focus groups agreed in a straightforward understanding of these two automation levels. Additionally, examples for each level (e.g., "automated crash avoidance" for some automation), and the connected icon to graphically represent automation in the discrete choice experiment were discussed in the focus groups. An example of the image that participants saw during one choice situation appears in Figure 1.

Attribute levels were combined into specific choice situations according to a Bayesian D-efficient design (Bliemer and Rose, 2010), with priors taken from a pre-test of the survey (with sample size N=100).

3.4 Elicited subjective discounting

As reviewed in Wang and Daziano (2015), laboratory and field time preferences experiments have been used in experimental economics to elucidate subjective discount rates. Expanding on the work of Newell and Siikamäki (2013), who implemented and used the Multiple Price List (MPL) method of Coller and Williams (1999) to analyze consumers' response to energy efficiency labels on water heaters, in our survey we implemented a modified version of the MPL method. MPL is organized as a series of binary choices between an immediate and a delayed reward, in which increasing exogenous discount rates are used to determine the values of the rewards (cf. Kirby et al., 1999). In our survey, only one binary choice was shown to participants at a time, with scenarios being displayed at an increasing interest rate. Assuming transitivity in intertemporal preferences, the experiment ended as soon as the respondent accepted the delayed reward, and the associated discount rate at the accepted delayed reward was set as the individual's subjective discount rate. Further details about the survey implementation of the MPL method (such as avoidance of immediacy bias) are discussed in Wang and Daziano (2015) with data from a pretest.

The elicited subjective discount rate resulting from the MPL experiment has a mean of 12.18 percent, standard deviation of 12.86 percent, and a median of 10 percent. Both the median and mean are higher than market interest rates for the automotive market, but are lower than some subjective discount rates that have been found using the endogenous discounting approach. Newell and Siikamäki (2013) in their experiment found a mean of 19 percent, standard deviation of 23 percent, and median of 11 percent.

As in Newell and Siikamäki (2013), we combine discrete choice models with the elicited intertemporal preferences, by calculating the expected present value of future costs as

$$\mathrm{PVFC}_{ij} = \mathbb{E}\left[\sum_{l=1}^{L_i} \frac{\text{operating cost}_{ij}}{(1+\rho_i)^l}\right], \tag{6}$$

where L_i is the total ownership time stated in the survey by individual i, ρ_i is the elicited subjective discount rate, and $\mathbb{E}$ is the expectation operator.[19]

[19]Our measure of the present value of fuel costs does not consider lifetime fuel costs since we do not survey whether respondents perceive fuel costs beyond their ownership period. If survey respondents value these costs beyond their ownership period–for example, if they expect to sell their vehicle and when they sell, they expect that fuel costs are capitalized in used vehicle prices – then our measure of fuel costs will be an underestimate of the respondents' expectations. This will lead us to overestimate WTP of the present value of fuel costs. We expect this bias to be small since a large majority of fuel costs are incurred during the initial years of ownership. Furthermore, no prior papers directly examined whether households value post-ownership fuel costs when purchasing a new vehicle, although indirect evidence indicates that used vehicle markets do capitalize these costs (Allcott and Wozny, 2014; Busse et al., 2013; Sallee et al., 2016).

4 Model Specification, Estimation, and Inference

4.1 Base models

In Table 4 we report estimates for our benchmark conditional logit model with fixed coefficients defined in Equation (1). We provide three separate versions of the model, with each version having a different method of defining fuel costs. In the first two versions, we replace the present value of fuel costs with alternative measures of fuel cost. The first version allows fuel cost to enter as a *monthly cost*, which is based on the respondent's expected amount of monthly driving and the cost per mile attribute.[20] The second version is only the *cost per mile as a simple attribute*. The third version includes the *expected present value of fuel costs* (PVFC) as a function of the respondent's elicited discount rate, expected length of ownership, expected amount of driving during ownership and the cost per mile attribute. We note that to avoid convergence issues in the search for the maximum likelihood estimate, different tables may scale the attributes differently. The actual scale for each attribute is discussed in the notes under each table.

In each model, the coefficients on the vehicle attributes are estimated to have the expected sign. We report these coefficients in the first panel of Table 4. Respondents dislike higher purchase prices, higher operating costs, and longer charging times and like longer ranges and both levels of automation. Purchase price sensitivity has a point estimate ranging from -0.77 to -0.772 and enters significantly at the 5 percent confidence level in each model. All three forms of operating costs enter significantly and with the expected negative sign. Preference parameters for both forms of automation are statistically significant at the 5 percent confidence level, where both forms are preferred over no automation and where full automation is preferred over partial automation.

To convert the preference parameters into dollar terms, we compute willingness to pay for an additional unit of each attribute by dividing the marginal utility of each attribute by the marginal utility of purchase price. Respondents are willing to pay about \$34 in a higher purchase price to reduce the monthly operating cost by \$1. This willingness to pay approximately represents a three-year payback window, which is consistent with recent survey evidence on the consumer valuation of fuel

[20]We model expected monthly driving as exogenous to the choice made by each respondent. This is consistent with assumptions made in Allcott and Wozny (2014).

costs (Greene et al., 2013).[21]

Respondents are willing to pay slightly more than \$3,500 for partial levels of automation and about \$4,900 for full automation. Are these estimates plausible? The estimate of willingness to pay for partial automation appears close to the reported price for Tesla's autopilot system available for \$3,000, which was announced a couple of weeks after the survey data were collected. The cost of downloading this system has since been increased to \$3,500.[22] This autopilot system is closer to our partial automation option as it involves software that helps avoid collisions from the front or sides or from leaving the road. The only fully autonomous package that appears close to market is an add-on package called Cruise RP-1, which is a driving program capable of full automation on certain highways. The current price tag for this program is \$10,000.[23]

4.2 WTP models using parametric and semi-parametric heterogeneity distributions

The base models were extended to mixed logit specifications in preference space. Table 5 presents the results of a mixed logit model where key parameters are normally distributed, where we interact key parameters with respondent characteristics, and where some parameters are normally distributed and others are log-normally distributed. For the model with respondent characteristics interactions, interactions of sociodemographics with the levels of automation were considered to determine potential deterministic preference variations.[24] To compute WTP for automation and other variables, we estimate a fixed parameter for vehicle purchase price then divide the preference parameters by the purchase price parameter.

[21] The empirical literature on how consumers value fuel cost savings is mixed and varies widely depending on method, time span, and unit of analysis (Greene, 2010). Several recent studies in the economics literature that leverage variation in gasoline prices, however, suggest that consumers fully value or only slightly undervalue fuel cost savings in new vehicle markets and only moderately undervalue these savings in used vehicle markets (Allcott and Wozny, 2014; Busse et al., 2013; Sallee et al., 2016).

[22] Source: `https://electrek.co/2016/08/24/tesla-quietly-increases-price-autopilot-new-hardware/`

[23] Source: `https://www.wired.com/2014/06/cruise-self-driving-car-startup/`

[24] Interactions between respondent characteristics and vehicle attributes represent how preferences for vehicle attributes vary according to respondent characteristics, e.g., high income households may prefer electric vehicles more than low income households.

In the column labeled MIXL-N, we estimate normally distributed coefficients for the natural log of range, charging time, and the two levels of automation. The parameter estimates with (μ) next to them represent estimates of the mean of each coefficient, while the parameter estimates with (σ) next to them represent estimates of the standard deviation of each coefficient. Each coefficient has the expected sign, as respondents dislike higher prices, higher fuel costs and greater charging times while they like longer ranges and automation. The implied WTP for both levels of automation are large and significant. Both, however, are substantially smaller than the estimates from our fixed coefficient logit models in Table 4. Furthermore, the mean WTP for the first level of automation, $1,453, exceeds the mean WTP for the second level of automation, $990, which is unexpected and runs contrary to our benchmark model results.

In the column labeled MIXL-N-OH, we present results of the same model but with respondent interaction terms. We interact the two levels of automation with several respondent characteristics: whether the respondent has heard of the Google car, whether the respondent is male, the number of years of experience driving, and geographic region.[25] The implied WTP estimates for this model seem more plausible. For some subsets of households, however, the implied WTP is much higher than the average estimates from the models in Table 4. For example, we estimate that wealthy female respondents living in the Midwest with little driving experience that have heard of the Google car are willing to pay in excess of $20,000 for full automation technology. This seems plausible given the degree of differentiation among household preferences.

In the next two columns labeled MIXL-LN-I and MIXL-LN-II, we present models for results where we assume the coefficients for both levels of automation are log-normally distributed. We report the implied mean of these distributions. Our estimates indicate that respondents are willing to pay about $1,000 for either level of automation. Note that all of the models with parametric heterogeneity fit the choice data better than the conditional logit specifications, as indicated by comparing the log likelihood values for the models. The log likelihood values for the parametric heterogeneity models range from -10,699 to -10,277, which are significantly higher than the values for the conditional logit specifications, which range from -12,466 to -12,415.

[25]Urban/suburban/rural interactions were tested, but no significant differences were found.

We summarize the estimates for willingness to pay for automation from the parametric heterogeneity models in Figure 2. The left and right panels in Figure 2 show the distribution of willingness to pay for the first and second levels of automation, respectively. We can see from both panels that the heterogeneity in WTP is large, even for the log normal specifications. These estimates are at odds with our fixed coefficient model estimates and are likely driven by model fit. This motivates the use of more flexible methods for estimating heterogeneous preferences for automation, which we explore next with estimates from semi-parametric discrete-continuous mixture models.

Table 6 presents the results of mixed-mixed multinomial logit specifications with three classes. For the column labeled Class 1, class assignment is set as base, whereas for Classes 2 and 3, class assignment is a function of socioeconomic covariates. For example, the respondent stating that he or she has heard of the Google car increases the likelihood that the respondent has preferences represented by Class 2 or Class 3, as inferred by the positive coefficient for the Google car covariate for these classes. Class 1 includes slightly less than a third of the sample at 29 percent and Class 3 includes slightly more than a third at 38 percent.

As expected, each class dislikes higher prices and fuel costs and likes longer driving range. The classes, however, have extremely different preferences for automation. Class 1 respondents have a mean estimate for WTP for automation that is not statistically different from zero. These respondents vary widely in their WTP for both types of automation, with each having a standard deviation higher than $10,000. This class is likely composed of households that are not aware of driverless car technology or are skeptical of the technology, as these households are less likely to have heard of the Google car and own fewer vehicles. Hence many households in this group are not willing to pay a positive amount for the technology.[26]

Class 2 respondents are, on average, willing to pay a substantial amount for automation. These respondents are willing to pay an average of $2,784 and $6,580 for partial and full automation, respectively. These values are in the range of the values from our benchmark estimates appearing in Table 4. This group of respondents appears to be eager to purchase automation technology once it becomes affordable. Their preferences are driven by knowledge of the Google car, driving long distances,

[26]The variation in WTP could be caused by the design and presentation of the choice experiments. We thank a referee for suggesting this possibility.

vehicle ownership, and higher education. It is important to note that the standard deviation for full automation for Class 2 is statistically significant and is \$15,526, which is more than twice as large as the point estimate for the mean. This implies that some respondents in this group remain skeptical of the technology and are not willing to pay anything for it. On the other hand, the large standard deviation implies that some respondents are willing to pay large sums of money–on the order of \$10,000–for full automation. Households in the United States that share preferences with these respondents will likely be the first to adopt fully autonomous vehicles when they become commercially available.

Class 3 respondents appear to have moderate desire for automation and represent a middle group between Classes 1 and 2. This group, which includes the largest number of respondents, is willing to pay \$1,187 and \$1,422 for partial and full automation, values that are substantially less than mean WTP for Class 2 and are less than the mean WTP for both groups of automation from our benchmark models. This group appears to be composed of individuals who have heard of the Google car and that have driving experience. Class 3 individuals are also more likely to be married and prefer driving. The price of automation must drop dramatically before this group completely adopts the technology. Similarly to individuals in Classes 1 and 2, individuals in Class 3 vary considerably in their preferences for automation, as the standard deviation estimates for both types are large and statistically significant. This result solidifies the notion that because automation is a relatively new technology, preferences for the technology will vary widely until it becomes more mainstream and consumers gain experience with it. Based on log likelihood values, the mixed-mixed logit model appears to have the best fit of the data among all of the types of models considered, with a log likelihood of -9,075.5.

We plot the implied distributions of WTP for both levels of automation in Figure 3. Similar to our results from models with parametric hetergeneity, these distributions illustrate that households vary considerably in their desire for autonomous features. Furthermore, these distributions appear more intuitive than those from the parametric heterogeneity estimates. The mean estimates of each distribution have the following intuitive appeal. The average Class 1 household dislikes automation and especially dislike full automation; the average Class 2 household is willing to pay a high premium for automation, especially full automation; the average Class 3 household is willing to pay a modest amount for either type of automation. These results, which are not obvious from the models with parametric heterogeneity, suggest a fairly even segmentation of the demand for automation, where about one-third of the population highly desires the technology, one-third has mild interest, and one-third does not want the technology.

5 Conclusions

We have taken an initial attempt to quantify how households currently perceive and value automated vehicle technologies. Our work has combined current discrete choice experimental methodologies with recent developments in the discrete choice literature to quantify how much households are willing to pay for multiple levels of automation. One strength of our approach is that we are able to have full control over attributes of alternatives faced by consumers, which allows us to identify how consumers value attributes not yet fully available in the new vehicle market, namely multiple levels of automation. Currently, only a few vehicles offer any form of automation, and the types of automation are not observed in standard datasets of vehicle attributes.[27] This makes a revealed preference approach to identifying how consumers value automation impossible until this attribute becomes more widely available in the market for new vehicles and observable to researchers.

We estimate that the average household is willing to pay a significant amount for automation: \$3,500 for partial automation and \$4,900 for full automation. Our estimate for WTP for full automation differs from the estimate found in Bansal et al. (2016). Differences in WTP estimates stem from two differences in methodology. First, Bansal et al. estimate preferences for an unrepresentative sample of the U.S. population, while our sample is representative along many observed household demographics. Second, Bansal et al.'s empirical model is based on a stated preference experiment that does not include an option for selecting a vehicle with conventional (non-autonomous) technology. In sharp contrast, in our choice experiments, many of the cases include at least one option that has no automation technology. We believe that this feature of our experiments is crucial to elicit how respondents trade off other attributes that differ between alternatives with and without automation.

We also find that households vary widely in their valuation of the technology. Some are not willing to pay anything for either type. Others that are more knowledgeable about current abilities of automation are willing to pay a great

[27] For example, in the Ward's Automotive vehicle characteristics data, we do not observe automation features.

deal for full automation; we estimate that a significant fraction of households are willing to pay above $10,000 for full automation. In our semiparametric random parameter logit specifications, we estimate that the demand for automation is split approximately evenly between high, modest and no demand, highlighting the importance of modeling flexible preferences for emerging vehicle technology. This variation may stem from a large difference in understanding of the technology, given that various forms of automation are relatively new vehicle attributes. Alternatively, the variation may be a product of the design of our choice experiments. In future work, we plan to alter the design of the experiments–by offering more alternatives to choose from, offering more levels of automation, or presenting precise forms of automation – to test this hypothesis.

A weakness of our approach, which is common to all discrete choice experiments, is that respondents in our study are making hypothetical choices that may not perfectly correspond to the choices they would make when purchasing a vehicle. Nevertheless, given the plausible magnitudes of the estimates of WTP for automation that we have found, we believe that the discrete choice experiment approach adopted here provides useful information to policymakers for better understanding and predicting the market penetration of this technology.

We suggest proceeding in this area of research with caution, given our estimates and the highly diverse preferences for automation as evidenced by the extremely large standard deviations of the random parameters. However, we expect to see less extreme heterogeneity as automated technology matures in the market, knowledge of the technology spreads, and consumers learn about its benefits and costs.

Acknowledgments

This research is based upon work supported by the National Science Foundation Award No. CMMI-1462289.

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A Tables

Table 1: Sample Demographic Statistics

Variable	Mean (S.D.)
Household size	2.717 (1.32)
Age of respondent	47.565 (13.55)
Number of children	1.41 (1.36)
Household income (2014$)	61,226 (42,135)
Years respondent has held license	25.409 (9.98)
Number of household members with license	1.914 (0.74)
Number of vehicles held by household	1.592 (0.79)
Respondent daily one-way commute (miles)	13.903 (12.72)
Respondent characteristics	**Percentage**
Male	50.49
Female	49.51
Married	54.49
Widowed	2.94
Divorced	13.70
Single	21.45
Living with partner	7.42
White	85.24
Black	8.32
Hispanic	7.18
Asian	2.934
High school diploma	98.613
Some college experience	76.84
Bachelor's degree	38.25
Master's or professional degree	12.40
Full-time ($\geq$ 30 hours per week) job	66.40
Part-time job	8.64
Homemaker	7.83
Student	0.90
Retired	10.44
Unemployed but actively looking for work	5.79
Household income $\leq \$30,000$	22.43
Household income $> \$30,000$ and $\leq \$60,000$	34.01
Household income $> \$60,000$ and $\leq \$90,000$	23.82
Household income $> \$90,000$	19.74

Note: The white, black, Hispanic and Asian percentages sum to more than 100 percent because some of the respondents have multicultural backgrounds.

Table 2: Vehicle Holdings Statistics

Variable	Coupe	Convertible	Sedan	Wagon	Hatchback	CUV	Truck	SUV	Van	Average
Age	5.93	8.14	6.57	6.13	7.71	4.43	10.36	8.32	6.77	7.00
	(4.46)	(3.28)	(4.82)	(4.39)	(4.95)	(3.48)	(4.74)	(4.41)	(3.49)	(4.76)
Miles per gallon	26.98	23.95	27.89	26.68	29.82	23.68	19.77	18.76	20.97	24.99
	(4.19)	(2.69)	(5.71)	(3.92)	(4.64)	(2.67)	(2.56)	(2.40)	(1.16)	(5.69)
Weight (lb.)	3,044.3	3,505.7	3,184.0	3,080.6	2,759.8	3,644.9	3,900.8	4,257.5	4,223.4	3,456.6
	(441.8)	(762.6)	(458.2)	(310.3)	(459.6)	(523.0)	(647.2)	(690.9)	(309.2)	(682.3)
Horsepower	185.74	195.36	171.88	159.80	146.91	196.87	193.33	224.46	219.74	186.56
	(72.37)	(80.12)	(50.40)	(32.58)	(58.77)	(48.67)	(52.53)	(53.96)	(40.98)	(57.75)
Torque (lb.-ft.)	182.99	219.14	177.99	163.87	157.02	202.62	230.66	250.53	232.39	197.82
	(72.74)	(128.39)	(56.27)	(41.50)	(65.27)	(63.28)	(59.06)	(59.66)	(32.32)	(66.68)
Footprint (sq. in.)	7,455.7	7,181.9	7,644.6	7,117.1	7,004.1	7,814.7	9,041.3	8,365.3	9,064.5	7,906.5
	(508.7)	(696.5)	(615.5)	(505.0)	(565.8)	(675.0)	(1356.5)	(1005.2)	(389.0)	(959.6)
Real MSRP (2014$)	31,336	58,654	26,197	24,446	21,396	27,695	23,869	33,715	29,634	27,980
	(36,990)	(98,073)	(11,810)	(8,788)	(9,656)	(7,203)	(5,024)	(8,026)	(4,328)	(19,616)
Annual VMT	14,225	13,571	15,018	16,167	14,031	14,846	16,828	16,884	16,908	15,236
	(10,994)	(15,542)	(12,738)	(10,516)	(14,371)	(11,490)	(15,144)	(13,787)	(13,546)	(12,869)
Holdings share (%)	13.23	1.17	40.79	1.26	4.10	12.23	11.06	11.39	4.77	100

Notes: We assign trim-level miles per gallon, weight, horsepower, torque, footprint and Real MSRP based on vehicle characteristics from Ward's Automotive and inflation rates from the Bureau of Labor Statistics. Vehicle age and annual VMT are based on two questions in our survey. With-in group standard deviation of each variable are reported in parentheses below the mean. Real MSRP is the Manufacturer's suggested retail price of a brand new version of the vehicle, adjusted for inflation. Since the vehicles held are of different model years, we convert all prices to 2014 dollars using historical inflation rates. Annual VMT stands for annual vehicle miles traveled. Vehicle footprint is defined as the product of a vehicle's wheelbase and its width, which is approximately equal to the rectangular area between a vehicle's tires. The characteristics weight, torque, and footprint are measured in pounds, pounds per foot, and square inches, respectively.

Table 3: Attributes and Attribute Levels for the Vehicle Choice Experiment

Attribute	Levels
Cost to drive 100 miles [$]	HEV: 7.0, 8.8 PHEV: 5.5, 6.5 BEV: 3.2, 4.0 GAS: 15.2, 15.8
Purchase price [$]	HEV: 125%, 170% of reference[a] PHEV: 145%, 185% of reference BEV: 130%, 200% of reference GAS: 100%, 110% of reference
Electric driving range [miles]	PHEV: 15, 40 BEV: 80, 150
Recharging time [hours]	PHEV: 2, 4 BEV: 1.5, 8
Autopilot package	No automation, some automation, full automation

Notes: The four alternatives available for the respondent to choose include a hybrid electric vehicle (HEV), a plug-in hybrid electric vehicle (PHEV), a battery electric vehicle (BEV), and a gasoline vehicle (GAS). See Figure 1 for an image of what respondents saw when making the vehicle choice. The reference purchase price is calculated from purchase price thresholds stated by the respondents.

Table 4: Conditional Logit Models

	Montly cost		Cost per mile		PVFC	
	Est.	SE	Est.	SE	Est.	SE
			Parameter estimates			
Price	**-0.076**	0.004	**-0.076**	0.004	**-0.076**	0.004
ASC BEV	**-0.851**	0.098	**-1.303**	0.242	**-0.602**	0.096
ASC HEV	-0.068	0.053	**-0.393**	0.166	**0.106**	0.051
ASC PHEV	-0.126	0.143	**-0.427**	0.201	0.022	0.142
Ocost	**-0.004**	0.000				
Cost			**-0.079**	0.021		
PVFC					**-0.242**	0.049
log*(range)*	0.073	0.048	**0.107**	0.052	0.048	0.048
Charging time	-0.002	0.009	-0.001	0.009	-0.003	0.009
Automation 1	**0.267**	0.034	**0.267**	0.034	**0.266**	0.034
Automation 2	**0.372**	0.033	**0.372**	0.034	**0.371**	0.033
			Implied willingness to pay			
Ocost	**-$48.17**	5.209				
Cost			**-$10.34**	2.820		
PVFC					**-$0.32**	0.067
log*(range)*	$ 9.72	6.549	**$14.01**	6.993	$6.29	6.392
Charging time	-$31.58	116.409	-$7.49	115.664	-$43.95	114.980
Automation 1	**$3,538.00**	502.423	**$3,498.31**	494.890	**$3,486.71**	495.980
Automation 2	**$4,916.76**	541.311	**$4,863.83**	533.248	**$4,850.39**	532.820
LL	-12,415		-12,466		-12,461	
AIC	24,847		24,950		24,939	
BIC	24,912		25,015		25,004	
McFadden's $\rho^2(0)$	0.087		0.083		0.084	
McFadden's $\rho^2(ASC)$	0.033		0.029		0.030	

Notes: Price is in thousands of dollars, operating cost (Ocost) is in dollars, cost is in cents, PVFC is in ten thousands of dollars, log(range) is the natural log of miles of range, charging time is in hours, and automation 1 and automation 2 are dummies for partial and full automation. The standard errors of the point estimates for WTPs are obtained using delta method. WTP of log(Range) corresponds to the marginal WTP for a baseline driving range of 100 miles. AIC is computed as $-2LL + 2 \times K$, and BIC as $-2LL + \log(NT/J) * K$, where K is the number of parameters. Bold estimates are statistically significant at 5%.

Table 5: Models with Parametric Heterogeneity

	MIXL-N				*MIXL-N-OH*				*MIXL-LN-I*				*MIXL-LN-II*			
	Est.	SE	WTP	% > 0	Est.	SE	WTP	% > 0	Est.	SE	WTP	% > 0	Est.	SE	WTP	% > 0
Price	**-0.111**	0.005			**-0.111**	0.005			**-0.091**	0.005			**-0.073**	0.004		
ASC BEV	**0.846**	0.133			**0.855**	0.133			**0.435**	0.123			**0.877**	0.100		
ASC HEV	**0.385**	0.065			**0.403**	0.065			-0.069	0.057			**-0.403**	0.056		
ASC PHEV	**1.767**	0.207			**1.773**	0.207			**1.302**	0.193			**2.408**	0.110		
PVFC	**-0.243**	0.068	**-$0.22**		**-0.230**	0.068	**-$0.21**		**-0.292**	0.062	**-$0.32**		**-0.346**	0.063	**-$ 0.47**	
log(Range) (μ)	**0.783**	0.072	**$70.57**	77%	**0.778**	0.072	**$69.96**	77%	**0.760**	0.068	**$ 83.07**	79%	**2.907**	0.140	**$ 34.51**	53%
Charging time (μ)	**-0.210**	0.018	**-$1,893.52**	28%	**-0.213**	0.018	**-$1,917.68**	28%	**-0.182**	0.016	**-$1,986.86**	28%	**-0.117**	0.015	**-$1,606.24**	33%
Automation 1 (μ)	**0.161**	0.047	**$1,453.14**	55%	0.063	0.144	**$6,322.84**		**0.543**	0.037	**$956.32**		**0.537**	0.037	**$1,022.89**	
Automation 2 (μ)	**0.110**	0.052	**$989.75**	52%	0.209	0.148	**$10,188.95**		**0.830**	0.034	**$ 935.06**		**0.912**	0.039	**$1,046.15**	
log(range) (σ)	**1.058**	0.031	**$9,532.37**		**1.043**	0.030	**$9,372.10**		**0.941**	0.028			**7.053**	0.822		
Charging time (σ)	**0.354**	0.015	**$3,184.50**		**0.358**	0.015	**$3,214.68**		**0.313**	0.014			**0.264**	0.014		
Automation 1 (σ)	**1.360**	0.071	**$12,251.70**		**1.339**	0.071	**$12,039.98**		**0.681**	0.058			**0.696**	0.060		
Automation 2 (σ)	**1.792**	0.069	**$16,144.62**		**1.761**	0.069	**$ 15,827.21**		**1.908**	0.281			**2.305**	0.400		
Autom1× Google car?					**0.245**	0.086	**$2,206.05**									
Autom1× Male					**-0.212**	0.079	**-$1,903.14**									
Autom1× log(income)					**0.165**	0.055	**$1,483.92**									
Autom1× years driving/10					**-0.138**	0.038	**-$1,241.47**									
Autom1× West					**0.429**	0.111	**$ 3,852.15**									
Autom1× Midwest					**0.481**	0.101	**$ 4,320.95**									
Autom1× Northeast					0.108	0.105	$972.40									
Autom2× Google Car?					**0.464**	0.087	**$4,167.07**									
Autom2× Male					**-0.164**	0.081	**-$1,476.46**									
Autom2× Log(Income)					**0.225**	0.054	**$2,023.78**									
Autom2× Years Driving/10					**-0.230**	0.040	**-$2,069.72**									
Autom2× West					0.205	0.115	$1,838.86									
Autom2× Midwest					**0.258**	0.102	**$2,322.13**									
Autom2× Northeast					-0.184	0.109	-$1,651.46									
LL	-10,277				-10,242				-10,583				-10,610			
AIC	20,579				20,538				21,192				21,245			
BIC	20,673				20,733				21,286				21,339			
McFadden's $\rho^2(0)$	0.244				0.247				0.222				0.220			
McFadden's $\rho^2(ASC)$	0.200				0.202				0.176				0.174			

Notes: Price is in thousand of dollars, PVFC in ten thousand of dollars, log(range) is the natural log of miles of range, and charging time is in hours. All models were estimated holding price, PVFC and ASCs fixed. MIXL-N model assumes all the parameters as normally distributed. MIXL-N-OH model assumes all the parameters as normally distributed and Automation 1 and 2 normally distributed with observed heterogeneity. MIXL-LN-I model assumes log(range) and charging time as normally distributed, whereas Automation 1 and 2 as log-normally distributed. MIXL-LN-II assumes charging time as normally distributed, whereas log(range) Automation 1 and 2 as log-normally distributed. The mean and SD of log normally distributed parameters represent the point estimates of μ and σ, where $\beta_i \sim LN(\mu, \sigma)$. The standard errors of the point estimates for log-normally distributed parameters are obtained using delta method. WTP of log(range) corresponds to the marginal WTP for a baseline driving range of 100 miles. WTP of log-normally distributed parameter evaluated at the median. 500 Halton draws for each individual were used to simulate the probability. AIC is computed as $-2LL + 2 \times K$, and BIC as $-2LL + \log(NT/J) * K$, where K is the number of parameters. Bold estimates are statistically significant at 5%.

Table 6: Models with No Parametric Heterogeneity

	Class 1				*Class 2*				*Class 3*			
	Est.	*SE*	*WTP*	% > 0	*Est.*	*SE*	*WTP*	% > 0	*Est.*	*SE*	*WTP*	% > 0
					A: Mean and standard deviations							
Price	**-0.119**	0.018			**-0.043**	0.005			**-0.227**	0.012		
ASC BEV	**-2.328**	0.580			**1.796**	0.157			**-0.624**	0.260		
ASC HEV	**-2.663**	0.204			**1.151**	0.117			**2.788**	0.160		
ASC PHEV	**-2.320**	0.973			**2.256**	0.221			**1.422**	0.392		
PVFC	**-0.747**	0.126	**-$0.63**		**-0.344**	0.153	**-$0.80**		-0.168	0.137	-$0.07	
log*(Range)*	**0.685**	0.339	**$57.56**		0.039	0.067	**$9.13**		0.022	0.137	$0.99	
Automation 1 (μ)	-0.072	0.325	-$607.49	48%	**0.119**	0.051	**$2,784.15**	100%	**0.269**	0.082	**$1,186.76**	67%
Automation 2 (μ)	-0.506	0.347	-$4,248.05	38%	**0.281**	0.053	**$6,580.23**	66%	**0.322**	0.083	**$1,422.42**	59%
Automation 1 (σ)	**1.231**	0.300	**$10,342.25**		0.022	1.462	$508.26		**0.609**	0.144	**$2,686.01**	
Automation 2 (σ)	**1.612**	0.276	**$13,541.52**		**0.663**	0.088	**$15,526.13**		**1.469**	0.103	**$6,484.70**	
					B: Variables for class assignment							
Constant					-0.193	0.288			**-1.559**	0.270		
Days 80 miles					**0.128**	0.026			**0.080**	0.025		
Own a car?					**0.596**	0.156			0.192	0.133		
No. of vehicles					**0.211**	0.065			**0.133**	0.064		
Google car?					**0.794**	0.067			**0.407**	0.068		
Age/ 10					-0.041	0.045			**0.187**	0.045		
Male					0.106	0.064			**-0.293**	0.063		
Married					0.123	0.065			**0.333**	0.063		
No. of children					**0.120**	0.024			0.041	0.022		
Comp. college					**0.212**	0.075			-0.034	0.070		
High school					**-0.429**	0.084			**-0.615**	0.080		
Single family					-0.227	0.118			-0.091	0.126		
Apartment					**-0.783**	0.148			0.269	0.146		
Own a house					-0.040	0.079			0.012	0.079		
Years driving / 10					**-0.398**	0.059			**-0.450**	0.062		
Accident					**-0.168**	0.059			**0.215**	0.058		
Prefer driving					**0.299**	0.069			**0.451**	0.066		
Fulltime					-0.163	0.088			0.124	0.083		
Part time					-0.232	0.123			0.069	0.117		
Homemaker					**-0.515**	0.129			**-0.759**	0.129		
White					-0.130	0.083			**0.325**	0.090		
Conservative					**-0.415**	0.068			**0.154**	0.066		
Liberal					-0.056	0.078			**0.370**	0.078		
West					**0.462**	0.088			**0.320**	0.084		
Midwest					**0.480**	0.080			**0.474**	0.074		
Northeast					**0.302**	0.080			**-0.162**	0.079		
Urban					**0.163**	0.062			**-0.181**	0.060		
Log(income)					-0.013	0.046			**0.196**	0.049		
Shares for classes			29%				33%				38%	
LL							-9,075.5					
AIC							18,323					
BIC							18,941					
McFadden's $\rho^2(0)$							0.333					
McFadden's $\rho^2(ASC)$							0.293					

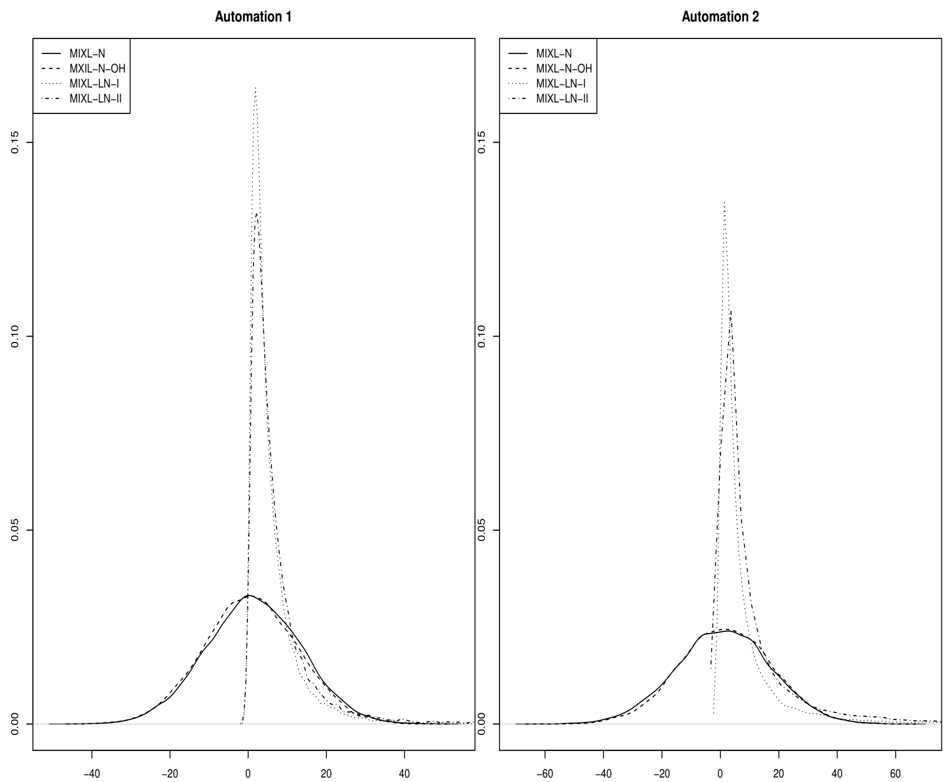
Notes: Price is in thousands of dollars, PVFC in ten thousands of dollars, log(range) is the natural log of miles of range, and charging time is in hours. WTP of log(range) corresponds to the marginal WTP for a baseline driving range of 100 miles. 500 Halton draws for each individual were used to simulate the probability. AIC is computed as $-2LL + 2 \times K$, and BIC as $-2LL + \log(NT/J) * K$, where K is the number of parameters. Bold estimates are statistically significant at 5%.

B Figures

Figure 1: Sample of a Choice Situation Presented to Respondents

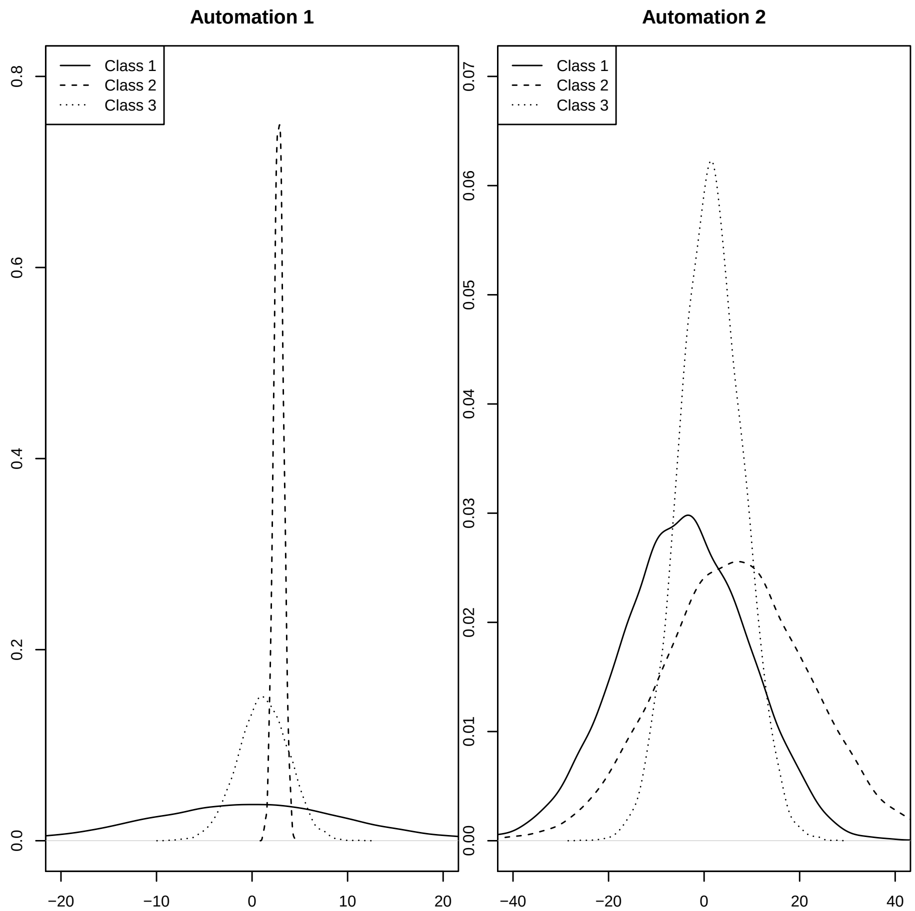
	Hybrid Vehicle HEV Gasoline	Plug-in Hybrid Electric PHEV Gasoline-Electricity	Electric Vehicle BEV	Gasoline Vehicle GAS
Cost to Drive 100 Miles	$8.80	$5.50	$3.20	$15.20
Price	$25,000	$37,000	$26,000	$20,000
Driving Range	590 miles Gasoline	15 miles / 520 miles Gasoline Only	150 miles Electricity	550 miles Gasoline
Refueling Time	5 minutes	2 hours / 5 minutes (electricity) (gas)	8 hours	5 minutes
Driverless Package	Some Automation	Full Automation	No Automation	No Automation

Figure 2: Willigness to Pay Distribution for MIXL Models



Notes: The horizontal axis measures WTP in thousands of dollars. Observed heterogeneity is evaluated at mean of variables.

Figure 3: Willigness to Pay Distribution for MM-MNL Model



Notes: The horizontal axis measures WTP in thousands of dollars. Observed heterogeneity is evaluated at mean of variables.