Discrete Heterogeneity in the Willingness to Pay to Increase Driving Range of Battery Electric Vehicles

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Abstract

This thesis presents a stated preference study of vehicle choice using survey data from 1226 respondents who were asked to indicate vehicle preference among: gasoline, hybrid, plug-in hybrid electric and battery electric vehicles. We estimated a latent class random utility model and used it to estimate the willingness to pay for three vehicle attributes: driving range, fueling/charging time and accessibility to fueling/charging infrastructure. Results showed that certain populations were enthusiastic to electric vehicles and were willing to pay on average $40-70 for a mile of additional driving range (100 miles as base). We confirmed that willingness to pay for driving range was diminished as driving range increased. The results were then applied to five electric vehicles on the market; low-end battery electric vehicles had leverages in making profit from improving driving range than high-end ones. Future battery improvements would strengthen the strategy of making profit from improving driving range.

Biographical Sketch

Sijia Wang was born in Jiangsu, China in 1993. She received her Bachelor's degree in Transportation Engineering from Southeast University in 2014. In August of 2014, she started her Master program in the School of Civil and Environmental Engineering at Cornell University. Her research interests were mainly in the area of transportation systems engineering, specifically on transportation demand modeling, transportation economics, and system optimization. She is going to join WSP|Parsons Brinckerhoff as a full time transportation engineer when she graduates.

To

The Continuous Support from My Family

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Chapter 1 Introduction

Growing concerns about energy security and climate change, along with advances in battery technology have stimulated a trending interest in electric vehicles, from a policy, economic and technology perspective. Back in 2008, with gas prices averaging nearly $4 a gallon, President Obama set a goal of getting one million plug-in vehicles on the road by 2015.[1] In his 2011 State of the Union Address, President Obama affirmed and highlighted this goal aimed at building U.S. leadership in technologies that reduce dependence on oil (Office of Energy Efficiency & Renewable Energy, 2011). Since then, his administration has backed billions of dollars in electric vehicle (EV) subsidies for consumers[2] and the industry[3] (Office of Energy Efficiency & Renewable Energy, 2011). Encouraged by these facts, along with advanced battery technology and recent successful stories in the development of EVs, automobile manufacturers have adopted and begun a trend of launching plug-in EVs. The industry continues to roll out new models in response to government mandates and its own ambition to create

[1] The President first announced this goal as a candidate in a speech in Lancing, Michigan on August 4, 2008. He first reiterated the goal as President at a speech in Pomona, California on March 19, 2009.

[2] The Recovery Act established tax credits for purchasing electric vehicles ($2,500 - $7,500 per vehicle, depending on the battery capacity) and conversion kits to retrofit conventionally powered vehicles with electric vehicle capability ($4,000 per vehicle, maximum). The President has also proposed transforming the existing $7,500 EV tax credit into a rebate that will be available to all consumers immediately at the point of sale.

[3] $2.4 billion in loans to three of the world's first electric vehicle factories in Tennessee, Delaware, and California. $2 billion in grants to support 30 factories that produce batteries, motors, and other EV components.

brands for environmental innovation. Yet today – with gas price near $2 a gallon – only about 400,000 electric vehicles have been sold (Inside EVs, 2016).

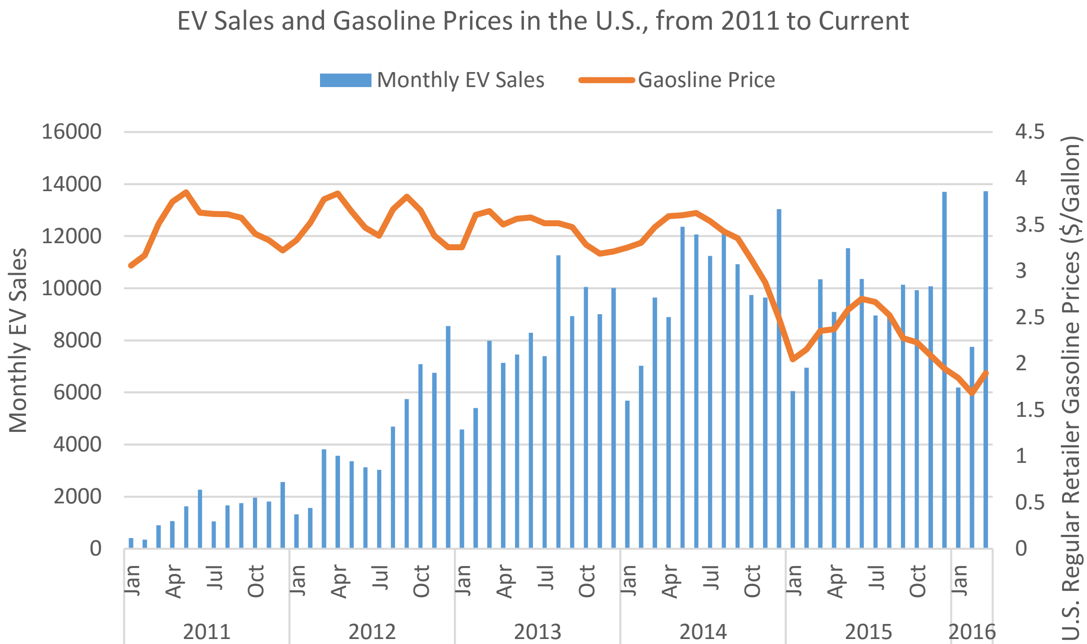


Fig.1 U.S. Monthly EV Sales and Regular Retail Gasoline Prices, Since 2011
Sources: (Inside EVs, 2016) and (U.S. Energy Information Administration, 2016)

There are several challenges that are preventing better sales of EVs. In fact, the main obstacles for EVs are their high purchasing price and short driving range; especially when the gasoline price is low, customers will switch gear to Internal Combustion Engine Vehicles (ICEVs) as they simply offer longer driving range[4]. Fig. 1 shows the monthly EV sales (Inside EVs, 2016) and monthly regular conventional retail gasoline prices (U.S. Energy Information Administration, 2016) in the U.S. since 2011. It can be

[4] Tesla CEO Elon Task said cheap oil will hurt EV sales according to FORTUNE report, Jan 2016. In Reuter report, Jan 2016, Energy Sec. Ernest Moniz said sales of electric vehicles (EVs) in the United States may not top one million until 2020.

observed from Fig. 1 that the rise and fall in monthly EV sales matched the fluctuation in gasoline prices. Last year, as the gasoline price kept going down, national EV sales fell 6 percent over the previous year, despite the industry offering about 30 EV models (Shepardson & Woodall, 2016).

On the bright side, green car advocates say EVs are a crucial part of the effort to reduce greenhouse gas emissions[5] (Michalek, Chester, & Samaras, 2012) and can help wean the U.S. off imported oil (Batlle, 2011). In the long term, they argue, oil price are almost certain to rise again which makes EVs more viable. GM chairman and CEO Mary Barra said she was convinced that consumers want EVs and that gas price would not stay low forever. Meanwhile, automakers are ambitious to make EVs more appealing by launching EVs with longer driving range. Besides, manufacturing cost is certainly going down because of the breakthroughs in the battery technology. EVs are still expected to have a good future. California, which is the most enthusiastic state in U.S. for EVs, accounted for about 40% of the total amount of EV sales in U.S. since 2011. It previously offered rebates of $2,500 for new battery-electric cars and $1,500 for plug-in hybrids, but beginning in March 2016, the amount will vary depending on the buyer's income. Governor Jerry Brown has called for cutting petroleum use in vehicles on California roads in half by 2030--a goal that was later turned into legislation. While

[5] Electric vehicles beat gasoline cars in cradle-to-grave emissions study, reported by Los Angeles Times, Nov 2015. http://www.latimes.com/business/autos/la-fi-hy-ucs-electric-vehicles-emissions-study-20151110-story.html

California leads the nation in electric-car sales, however, it will need to boost its current sales significantly to meet that target[6].

Motivated by these anticipations, the aim of this research is to verify them with survey data and econometric and engineering models, to test our hypotheses and, finally, to provide and support marketing directions for automakers. We are interested in the potential consumer demand for EVs and whether or not they can become an economic attractive alternative. To this end, we used data from a stated choice experiment to estimate how much consumers are willing to pay for EVs. In this research, we analyze demand for EVs using a discrete choice model with discrete heterogeneity distribution for the taste parameters. We focused on the willingness to pay for pure battery electric vehicles (BEVs) rather than plug-in hybrid vehicles (PHEVs). We addressed the current EV features such as high battery cost, short driving range, long charging time and limited recharging infrastructure. Recent advances in technology suggest that driving range can be extended, charging time shortened and battery cost lowered. After a few years of mass production, the unit cost for EVs is likely to fall. It seems to be the right time to take a look at the economic potential of EVs.

This research focuses on answering the following questions:

- Are auto consumers interested in EVs? To what extent?

[6] The amount of EV sales in California counts for one-third to one-half of all EV sales nationwide and it's expected to grow. http://www.greencarreports.com/news/1102251_how-many-electric-cars-does-california-buy-one-third-to-one-half-of-all-of-em

- Do auto consumers treat PHEV and BEV differently?
- Is there any sociodemographic characteristic which drives the intention of adopting or not adopting an EV (PHEV or BEV)? Such as gender, knowledge, income etc.
- How people value attributes of EVs? Can improving driving range be a possible strategy for automakers to boost both sales and profit? What about lowering manufacturing cost?

The remainder of this thesis is organized into five parts. Chapter 2 states relevant literature regarding the modeling approach to analyzing demand for EVs. Chapter 3 reviews the theory and formulation of latent class discrete choice models. Chapter 4 summarizes the survey data and model specification and presents the model estimates. Chapter 5 gives a case study with five BEVs to explain how results from our model can be applied in the automotive industry. Finally, chapter 6 gives conclusions and opportunities for future study.

Chapter 2 Recent studies on EV adoption

Given the early stage of development for alternative fuel vehicles, empirical revealed preference data from actual purchases have not been sufficiently accumulated (Brownstone, Bunch, & Train, 2000)[7]. Therefore, we adopted a stated preference (SP) method. SP data come from survey responses to hypothetical choices, which take into account certain types of market constraints useful for forecasting future changes in consumer behaviors. Most demand studies for EVs have used SP analysis in some form. Characteristics theory of value by Lancaster (1966) provided the theoretical basis of SP methods. Random utility maximization theory (McFadden, 1974) established the econometric foundations for their development and application. The earliest SP studies in the automotive market started in response to the 1970s oil crisis. Beggs et al. (1981) studied the potential demand for EVs by applying an ordered logit model to SP data in which individuals provided rank ordering for hypothetical vehicle descriptions. Calfee (1985) studied only the potential private demand for EVs, using discrete choice SP data and a fully disaggregated logit model. Train (1980) used a vehicle-type choice model (multinomial logit model developed by Lave and Train (1979)) to estimate the potential demand for EVs. Hensher (1982) focused on the demand elasticities for EVs in Sydney, Australia. Those researches examined

[7] Revealed preference (RP) theory is a method of analyzing choices made by individuals, mostly used for comparing the influence of policies on consumer behavior. RP models assume that the preferences of consumers can be revealed by their purchasing habits.

individual’s tradeoffs between vehicles’ purchase price, operating cost and driving range, while ignoring their sensitivity to variations in fuel availability and refuel time. U.S. studies of this period only surveyed on multi-vehicle households due to higher tolerance of range limitation. Their main conclusion was that EVs’ short driving range can indeed account for strong impediments to consumer adoption.

Another wave of EV studies happened in early 1990s due to the zero-emission vehicle mandate in California. These studies tried to predict the demand of EV in California. Bunch et al (1993) implemented a nested multinomial logit model with data from a mail-back based SP survey. Results indicated that range between refueling or recharging is an important attribute, particularly if range for an alternative fuel vehicle is substantially less than that for gasoline. Brownstone et al. (1996) used both RP and SP information from a mail-based survey. They used the standard multinomial logit model to explain the discrete choices. Their model forecasted the demand for future vehicles conditional on the current holdings of the household and involved vehicle transaction decision. Vehicle range was a very important concern to households when they buy alternative-fuel vehicles, refueling time seemed not too important from their estimates. Brownstone and Train (1999) compared multinomial logit and mixed logit models for data on California households' revealed and stated preferences for automobiles. The mixed logit models provided improved fits over multinomial logit that were highly significant, and showed large heterogeneity in respondents' preferences for alternative-fuel vehicles. The effects of including this preference heterogeneity were demonstrated in forecasting exercises. The 1990s studies had also added some novel elements in regard with the attributes relevant for alternative fuel vehicles such as refuel duration and timing, the availability of refuel infrastructure and air emissions. The majority of these studies find that all the aforementioned attributes are significant determinants of consumers' vehicle choice. Some of the 1990s studies went further to acknowledge that consumers' evaluation of driving range is not independent from the levels of refuel/recharge time and availability of fueling/charging infrastructure presented to them (e.g., Segal, 1995; Ewing and Sarigollu, 1998).

The first two waves of studies supported an explosive third wave, which instead has focused more on the trade-offs that control the potential adoption of EVs. The typical trade-offs involve purchase cost (e.g., Thiel et al., 2010; Daziano R.A., 2013), convenience (such as driving range, availability of charging stations and charging time, e.g., Dimitropoulos et al., 2013), operating cost and environmental utility (Mckinsey 2009). In particular, the willingness to pay for marginal improvements in driving range is an economic measure of the tradeoff between purchase price and driving range of electric vehicles, which is a key input for welfare and cost-benefit analysis of investments in improving electric batteries. Dimitropoulos et al. (2013) carried out a meta-analysis on the willingness to pay for marginal improvements in driving range.

Inference on willingness to pay can be derived from the estimates of discrete choice models. Among those researches, Sandor and Train (2004), Train and Sonnier (2005) and Hess et al. (2006) assumed both willingness to pay for and consumer surplus from improvements in driving range were constant. However, Kavalec (1999), Hess et al. (2012) and Daziano R.A. (2013) claimed that driving range should exhibit diminishing returns, which means an additional mile in driving range gives different marginal utility for vehicles with different scales of range. A number of additional studies are also conducted in California (e.g. Adler et al., 2003; Axsen et al., 2009; Nixon and Saphores, 2011). Table 1 provides a summary of different willing to pay estimates for a one-mile improvement in driving range in the U.S. market.

Table 1
Willingness to pay estimates for marginal improvements in driving range. Results from different studies in the US.

Main References	Market	WTP ($/mile)		
		Mean est.	Min est.	Max est.
Beggs and Cardell (1980)	US (1978)	85	61	132
Calfee (1985)	California (1980)	195	195	195
Bunch et al. (1993)	California (1991)	101	95	106
Golob et al. (1997)	California (1994)	117	76	202
Tompkins et al. (1998)	US (1995)	64	44	102
Brownstone et al. (2000)	California (1993)	99	58	202
Train and Hudson (2000), Train and Sonnier (2005)	California (2000)	100	87	131
Hidrue et al. (2011)	US (2009)	58	29	82
Nixon and Saphores (2011)	US (2010)	182	46	317
Hess et al. (2012)	California (2008)	43	36	49

Daziano (2013)	California (2000)	103	75	171

Source: Daziano R.A. (2013)

The stated choices resulted from such SP experiments have been analyzed on the basis of discrete choice models. As stated at the beginning of this chapter, discrete choice has been widely applied to analyze the demand for alternative fuel and electric vehicles. In the early period, most of the research (Bunch et al., 1993; Golob et al., 1997; Ewing and Sarigollu, 1998; Brownstone et al., 2000) used the multinomial logit model (MNL) (McFadden, 1974) or the nested logit model (Daly and Zachary, 1978; McFadden, 1978; Williams, 1977). However, these basic models have several shortcomings. The most notably is MNL's assumption of independence from irrelevant alternatives (IIA). The mixed logit model (McFadden and Train 2001; Hensher and Greene, 2003) stands out as one of the most significant extensions of the MNL model. Some comparison results from previous research (Brownstone and Train, 1999) showed that mixed logit models (MIXL) provided improved fits over MNL that were highly significant, along with large heterogeneity in respondents' preferences for alternative-fuel vehicles. Hidrue et al. (2011) used latent class model (LC) which resembles the mixed logit but assumes discrete preference heterogeneity instead of continuous distributions. LC can be viewed as a semi-parametric extension of the MNL and also a relaxation of MIXL due to its assumption of discrete distribution of taste parameters. Greene and Hensher (2003) contrasted MIXL and LC and they concluded that both models offer alternative ways of capturing unobserved heterogeneity and other potential sources of variability in unobserved utility. The LC has the virtue of being a semi-parametric specification which frees the analyst from possibly strong or unwarranted distributional assumptions about individual heterogeneity, whereas the MIXL provides the modeler a tremendous range within which to specify individual unobserved heterogeneity.

In this research, we modeled discrete choice with a LC to capture unobserved individual heterogeneity. We tested other models such as MNL, MIXL, MMLM (Mixed-mixed logit model), but the results were not reasonable. Results from other models are presented in Appendix B for further reference.

Chapter 3 Model explanation

3.1 Random Utility Maximization models

In economics, utility is a ubiquitous concept to measure the satisfaction attained when an individual performs certain activity, such as choosing a product or a service. The choice decision involved in most economic situations is based on subjective utility. When considering choosing a product, individuals compare the utility of each alternative product. Generally, we assume individuals are all rational so that they always choose the product or service which gives them the maximum utility (i.e. they are satisfied the most from their choices). Based on this nature, researchers can infer people's choices ideally by mapping consumers' preferences.

Effectively, due to the subjective nature of utility, we cannot directly observe nor calculate its exact value because it is unrealistic to observe or measure every characteristic of the individual, the product and the choice situation that compose and affect the choice decision. We can only estimate the utility and predict the choice from some observable information about the individual, the product and the choice situation. A random utility maximization model presumes that utility u_{in} provided to individual n by alternative i (from a total of J alternatives) can be decomposed into an observable deterministic part V_{in} and a random part ε_{in} which is unobservable, such that

$$u_{in} = v_{in} + \varepsilon_{in} \tag{1}$$

where $i \in (1,2,\ldots,J)$, $n \in (1,2,\ldots,N)$. v_{in} is the deterministic part of utility which comes from a set of observable attributes z_{in}. z_{in} is related to the attributes vector x_{in} of alternative i for individual n, maybe interacted with the characteristics vector w_{in} of individual n, so z_{in} can actually be a function $z_{in} = z(x_{in}, w_n)$. ε_{in} is the random part of utility which contains all the unobservable factors which also influence the individual's choice.

Let β denote the coefficient vector of the corresponding observable attributes z_{in}. Suppose z_{in} reflects v_{in} and enters utility function in a linear form, so that Eq. 1 can be then written as:

$$u_{in} = \beta' z_{in} + \varepsilon_{in} \tag{2}$$

According to random utility theory, the probability of alternative i chosen by individual n is

$$P_{in} = P(u_{in} \geq u_{i'n}, \forall i' \neq i)$$

$$= P(v_{in} + \varepsilon_{in} \geq v_{i'n} + \varepsilon_{i'n}, \forall i' \neq i)$$

$$= P(\varepsilon_{i'n} - \varepsilon_{in} \leq v_{in} - v_{i'n}, \forall i' \neq i) \tag{3}$$

where $v_{in} - v_{i'n}$ is also a deterministic value once given the choice situation, and $\varepsilon_{i'n} - \varepsilon_{in}$ is random. So P_{in} is the probability of random term $\varepsilon_{i'n} - \varepsilon_{in}$ below the corresponding value $\beta' z_{in} - \beta' z_{i'n}$, $\forall i' \neq i$. In sum, the choice probability is a cumulative distribution.

3.2 Multinomial Logit Model

MNL is used when the dependent variable is nominal and can be taken from more than two categories. It is widely applied in practice because generally there are more than two alternatives in the choice set. Multinomial logit assumes that there is no correlation among alternatives and the error term in the utility function is independent and identically distributed Gumbel (also known as type-1 generalized extreme value distribution). The choice probability for an MNL model takes the following form:

$$P_{in} = \frac{\exp(\beta' z_{in})}{\sum_{i'=1}^{J} \exp(\beta' z_{i'n})} \tag{4}$$

Based on random utility model, multinomial logit model assumes that data are case specific, and each independent variables has a single value for each choice situation. The independent variables are not necessarily statistically independent from each other. There might exist some collinearity among independent variables, but relatively low.

3.3 Latent class logit model

Multinomial logit model is a very restrict model because it does not consider any possible correlation among alternatives and among responses from the same individual. Latent class logit model takes unobserved preference heterogeneity into consideration. LC seeks to identify unobservable groups (clusters or classes) of individuals in the data that share similar preferences based on a parametric logit model for assignment to clusters.

Due to its flexibility, LC is used in this research. Latent class model assumes that individual choice depends on observable attributes and on latent heterogeneity through a model with discrete parameter variation. It assumes that individuals are sorted into Q classes, but which individual to which class is unknown both to the individual and the researcher. For each individual, the probability of being assigned into class q is determined by a set of observable characteristics which enter the model for class membership. Denote π_{iq} the probability of individual n being assigned to class q, then

$$\pi_{nq} = \frac{\exp(w_n^{'}\theta_q)}{\sum_{q^{'}=1}^{Q}\exp(w_n^{'}\theta_{q^{'}})}, \; q = 1,2,\ldots,Q \tag{5}$$

where w_n is the vector of observable variables for membership, which as mentioned before is the vector of a list of individual characteristic data. The parameters of one of the classes in Q are normalized to zero to ensure model identification.

If within a class, the conditional probability of person n choosing alternative i when he or she is in class q is actually a multinomial logit form as Eq. 4:

$$P_{in|q} = \frac{\exp(x_{in}^{'}\beta_q)}{\sum_{j=1}^{J}\exp(x_{jn}^{'}\beta_q)}, \; i, j = 1, 2, \ldots, J \tag{6}$$

Therefore, the unconditional probability of observing person n choosing alternative i would be:

$$P_{in} = \sum_{q=1}^{Q}\pi_{nq}P_{in|q} = \sum_{q=1}^{Q}\left(\frac{\exp(w_n^{'}\theta_q)}{\sum_{q^{'}=1}^{Q}\exp(w_n^{'}\theta_{q^{'}})} \times \frac{\exp(x_{in}^{'}\beta_q)}{\sum_{j=1}^{J}\exp(x_{jn}^{'}\beta_q)}\right) \tag{7}$$

3.4 Maximum likelihood estimation

The objective of building any kind of regression model is to fit the data and use the model for future prediction. We expect to maximize the likelihood function by selecting the set of model parameters, this maximizes the likelihood of estimating the right choice result given the data. The likelihood of observing the choices in the dataset is:

$$L(\beta,\theta;y_{in}\mid z_{in})=\prod_{n=1}^{N}\left(\sum_{q=1}^{Q}\pi_{nq}\left(\prod_{i=1}^{J}(P_{in|q})^{y_{in}}\right)\right) \tag{8}$$

And the log-likelihood, which is easier to maximize, is:

$$\ln L(\beta,\theta;y_{in}\mid z_{in})=\sum_{n=1}^{N}\left(\sum_{q=1}^{Q}\pi_{nq}\left(\prod_{i=1}^{J}(P_{in|q})^{y_{in}}\right)\right) \tag{9}$$

where $y_{in}=1$ if individual n chooses alternative i, and $y_{in}=0$ otherwise.

By maximizing the log-likelihood of observing the data in the sample and by changing the value of the parameters in the model until a maximum value of the likelihood is attained, we can obtain the maximum likelihood estimates:

$$\left(\hat{\beta},\hat{\theta}\right)=\arg\max L(\beta,\theta;y_{in}\mid x_{in})=\arg\max \ln L(\beta,\theta;y_{in}\mid x_{in}) \tag{10}$$

LC captures preference heterogeneity with differing preference parameters across classes; some classes may even have greater propensity for choosing a specific alternative than others. Shonkwiler and Shaw (2003) and Swait (2007) show that the LCM is not constrained by the IIA property of MNL. However, as pointed out by Greene and Hensher (2003) LC assumes independence of multiple choices made by the same individual.

Chapter 4 Survey data and model estimation

We use data from an online survey conducted U.S. nationwide in 2014, focusing on people's stated preference towards vehicles with different kinds of propulsion, which are a gasoline vehicle, hybrid vehicle, BEV and PHEV. There were three parts in the survey related to our EV study. First people were asked questions focusing on their current vehicle ownership and driving habits, and then they were randomly assigned 8 choice situations in which they had to choose the vehicle they preferred among four alternatives and finally they were asked to give personal information about themselves and their family. There were 1226 individuals who participated and completed the choice experiment in the survey, this gave us 9808 observations that we used to estimate LCM. Detailed summary of the survey questions is presented in the Appendix A.

4.1 Attributes of the alternatives

The survey had 16 different vehicle choice experiments. Every participant was asked to complete 8 choice experiments, which were randomly assigned to them. In each choice experiment, participants were asked to consider four vehicles: Gasoline Vehicle (GV), Hybrid Vehicle (HV), Electrical Vehicle (BEV) and Plug-in Hybrid Vehicle (PHEV). In correspondence with our objective, the attributes of vehicles in the choice experiments are: vehicle purchasing price, vehicle operating cost, driving range, fueling/charging time and accessibility of recharging station (network).

As a dominant factor affecting people's purchasing choice in daily life, vehicle purchasing price was introduced into the variables. Gasoline vehicle was designed as the cheapest car in every choice experiment. Vehicle operating cost is basically the fuel or electricity cost plus maintenance cost per 100 miles in U.S. dollars. Driving range is the maximum distance in miles the vehicle can travel after one full fueling or charging and without refueling or recharging. Most BEVs can only go about 80-150 miles between charging while GVs can go over 300 miles before refueling. For PHEVs, we only consider their driving ranges when powered from electric system. We use the logarithm of driving range to reflect its decreasing marginal effect on utility. Charging time is the time measurement in hours which gives the required amount of time vehicle needs to be fueled or charged from empty to full. Accessibility of the refueling station or network is a scaled variable which is in scale 0 to 100%. We use the density of gas station as the base 100%, the density of recharging station of BEV and PHEV is a ratio to that of gas station, which is below 100%.

Table 2 summarizes the values used in the choice experiments. GV has the cheapest purchasing price and highest operational cost. HV has the longest driving range and is more fuel efficient than gasoline vehicle. They both has the shortest refueling time and their refueling station density are 100% as base. BEV and PHEV are more expensive and have low operational cost.

Table 2
Summary of alternative attributes

	Gasoline option	Hybrid option	Electric option	Plug-in Hybrid option
Purchasing Price, $	15,500 16,500	19,000 21,000 26,000 28,000	20,000 21,000 31,000 33,000	22,000 24,000 29,000 31,000
Operating Cost, $/100 miles	15.20 15.80	7.00 8.80	3.20 4.00	5.50 6.50
Driving Range, mile	495 550	540 590	80 150	15 40
Fueling/Charging time, hour	5/60	5/60	1.50 8.00	2.00 4.00
Network, %	100	100	20 40 60 80	20 40 60 80

Until now, we have the variables which enters the model as x_{in}.

4.2 Sociodemographic characteristics

The survey was taken online by 1730 of US residents above 17 years old. After qualification and ad justification of the completed answers, the useable number of sample came down to 1226 adults countrywide.

Questions for individual's characteristics were asked. We expected there are effects from those sociodemographic characteristics. For example, younger people are expected to be bolder, more liberal and might be more open to new technology which might cause a higher adoption rate of non-conventional vehicle among them, but they also might earn relatively lower income which is an impedance for them to purchase a relatively more expensive vehicle. The older generations, on the other hand, are expected to be more conservative and might be less open to new technology, but they also might have more money to afford an expensive electric car.

Table 3 summarizes the sociodemographic variables as used in estimation. Most of the sociodemographic data are transformed into indicator variables.

Table 3

Definitions and descriptive statistics (N=1226) for variables used in LC model. Either % or mean is shown, depending on whether the variable is dichotomous or not.

Variable	Description	% in sample	Mean (SD)
Age	Individual age		47 (13)
Below40	1 if 18-40 years of age; 0 otherwise	32	
Above40	1 if 40-80 years of age; 0 otherwise	68	
Male	1 if male; 0 otherwise	50	
Married	1 if married; 0 otherwise	54	
Income	Household income, $1,000		61 (40)
Currgas	1 if current car is gasoline, 0 otherwise	94	
Currhyb	1 if current car is hybrid, 0 otherwise	3	
Currelec	1 if current car is electric, 0 otherwise	0.4	
Nvehadd	Number of additional car		1.3 (0.4)
Morethan2days 80miles	1 if travels over 80miles more than 2 days in a month , 0 otherwise	39	
Compcollege	1 if has complete college, 0 otherwise	53	
Hschorless	1 if has high school diploma or less, 0 otherwise	23	
Ownhouse	1 if family owns a house, 0 otherwise	70	
Singfamh	1 if lives in a single family house, 0 otherwise	76	
Apartment	1 if lives in an apartment, 0 otherwise	18	
Yrsdriving	Years of driving		25 (10)
Fulltime	1 if works as full time, 0 otherwise	66	
Parttime	1 if works as part time, 0 otherwise	9	
Hmaker	1 if works as home maker, 0 otherwise	8	
Student	1 if is a student, 0 otherwise	1	
Conserv	1 if is conservative, 0 otherwise	40	
Lib	1 if is liberal, 0 otherwise	22	
Independent	1 if is independent, 0 otherwise	38	
West	1 if lives in the west, 0 otherwise	17	
Midwest	1 if lives in the Midwest, 0 otherwise	24	
Northeast	1 if lives in northeast, 0 otherwise	21	
Childcnt	Number of children		1.4 (1.3)
Ownercar	1 if is the owner of car, 0 otherwise	96	
White	1 if is white, 0 otherwise	85	

4.3 Model Estimation

We estimated a latent class discrete choice model using the choice microdata collected in the survey. We are going to discuss about the class membership assignment and the random utility part of LCM separately. After getting the estimates of the parameters, we derived the willingness to pay for vehicle attributes.

4.3.1 Random utility model estimation

The random utility portion of the model is show in Table 4. We estimated the model with 2, 3 and 4 latent classes. With more classes, the value of parameters seems to have deteriorated and some of the models did not even converge. This indicated that a model with 2 latent classes was good enough. Two latent class models are compared. One of these two models has more individual characteristics as membership assignment variables. The main difference between the two is how much of the information we observed can be applied to the model and still have a reasonable explanation for the outcome. On the one hand, we might prefer more reasonable sociodemographic data entering into the model, which is model A. On the other hand, producing a model which gives more information simply by adding more variables might also cause an over fitting problem. In case of over fitting, we considered Bayesian Information Criteria (BIC) for each latent class model. The Bayesian Information Criteria penalizes more for a higher number of variables. In this case, model B is preferred.

The two models do not differ too much regarding the values of the estimated preference parameters. As expected, the negative and significant parameters for vehicle purchasing price, operating cost and charging time indicate that vehicles with higher purchasing price, higher operating cost and longer charging time are less likely to be chosen. The positive and significant parameter of log driving range and network indicate that vehicles with longer driving range and higher accessibility of recharging station would be preferred by the individuals. These effects are common in every class of each model.

Table 4
Random utility model estimates for two LCMs

Parameters	Model A Estimates (Std. Error)	t-stats	Model B Estimates (Std. Error)	t-stats
Class 1				
Electric Constant	0.9605	2.1683	1.0469	2.3790
	(0.4430)		(0.4401)	
Hybrid Constant	-0.5156	-1.7321	-0.4586	-1.5529*
	(0.2876)		(0.2953)	
Plug-in Hybrid	2.3384	6.9934	2.3899	7.1845
Constant	(0.3344)		(0.3326)	
Price	-0.0780	-14.0774	-0.0778	-14.1642
($,000)	(0.0055)		(0.0055)	
Operating Cost	-0.0720	-1.8867	-0.0648	-1.7094
($/month, 00)	(0.0381)		(0.0379)	
lnRange	0.3089	4.6953	0.3022	4.6257
(ln mile)	(0.0658)		(0.0653)	
Fueling/Charging	-0.0220	-2.1112	-0.0219	-2.1137
Time (hour)	(0.0104)		(0.0103)	
Network	0.4825	2.9969	0.4850	3.0214
(%)	(0.1610)		(0.1605)	
Class 2				
Electric Constant	4.1308	7.8123	3.9354	7.4481
	(0.5288)		(0.5284)	
Hybrid Constant	-0.5082	-1.4984*	-0.3834	-1.1265*
	(0.3392)		(0.3404)	
Plug-in Hybrid	2.7718	7.8123	2.6011	7.4481
Constant	(0.4454)		(0.4468)	
Price	-0.0597	-10.8866	-0.0593	-10.7690
($,000)	(0.0055)		(0.0055)	
Operating Cost	0.0441	1.0052*	0.0290	0.6851*
($/month, 00)	(0.0439)		(0.0440)	
lnRange	0.4047	5.5072	0.4037	5.4647
(ln mile)	(0.0735)		(0.0739)	
Fueling/Charging	-0.0322	-3.3229	-0.0319	-3.2752
Time (hour)	(0.0097)		(0.0097)	
Network	0.1520	0.7338*	0.1379	0.6651*
(%)	(0.2102)		(0.2073)	
Log-likelihood Value	-10871		-10878	
BIC	22174.94		22031.94	

*Parameter estimate is not significant at 90% confidence level

Inside each class, the alternative specific constant (ASC) indicates the intrinsic preference toward alternatives when all the attributes are the same. For example, in reality some people are naturally more resistant to adopt electric vehicles, they would have a strong preference for gasoline vehicles even when all the attributes of the available vehicles are the same. In our model, the alternative specific constant for conventional gasoline vehicle is normalized to zero as a base. The insignificant estimates of ASC for hybrid vehicles means there is no significant preference between hybrid vehicles and gasoline vehicles (everything else held constant). The positive and significant estimates of ASC for electric vehicles and plug-in hybrid vehicles suggests people prefer these two vehicles to gasoline vehicles. The larger the ASC is, the more favored the alternative is. The two classes in each model differ in the ASCs for electric vehicles and plug-in hybrid vehicles. People in class 1 prefer plug-in hybrid vehicles the most while people in class 2 prefer electric vehicles the most instead.

From the results, it is surprising that people in both class show a preference toward electric vehicles and plug-in hybrid vehicles than conventional vehicles. This is a good sign because EVs are more environmentally friendly. For our research, this might be a good sign for BEV and PHEV automakers. However, it could be that our sample contains environmentally-conscious consumers, and this results may not be representative of the average preferences in the population.

In the PHEV-oriented class, operating cost has a significant effect on people's choice decision. Generally, operating cost for PHEV is higher than BEV because it involves gasoline consumption sometimes and PHEV has a lower driving range when it only uses the propulsion from electric battery. The reason people prefer PHEV than GV is generally its lower operating cost and the consumer would like to see higher savings even though PHEV still may be burning gasoline. So people who are PHEV-oriented might care more about the operating cost. Network has a possible and significant effect on their choices because PHEV has the shortest driving range when powered by a battery system, which makes it important to have access to either fuel or charge on the road.

In the BEV-oriented class, accessibility of recharging station (network) is not significant even though it has the expected sign. BEV only uses power from its battery system. On the one hand, consumers may have thought they would charge at home, making the availability of charging stations less relevant. On the other hand, people who are BEV oriented might care less about recharging if BEV provides good driving range.

4.3.2 Membership model estimation

The parameters of PHEV oriented class are normalized to zero, so the parameters showed below refer to BEV oriented class. They represents the impact of an attribute on the probability of being assigned to the BEV oriented class. For example, the positive and significant parameter of age indicates older participants are more likely to be BEV oriented. Table 5 shows the class membership model results from model A and table 6 shows the results from model B.

Table 5
Model A - Class membership model estimates (Class 1 is normalized to zero)

Variables	Coefficient	T-stats	Odds Ratio
Class 2 Membership Constant	-1.1995	-3.8556	0.3
Morethan2days80miles	0.2115	3.8863	1.2
Nvehadd	0.0427	0.7860*	1.0
Childcnt	0.0179	0.9444*	1.0
Hispanic	-0.1513	-1.5770*	0.9
Ownercar	0.4445	3.5348	1.6
Currgas	0.7712	4.0755	2.2
Currhyb	0.2394	1.0432*	1.3
Currelec	-0.1389	-0.2877*	0.9
Age	0.0167	4.4257	1.0
Male	0.1964	3.8475	1.2
Married	0.1831	3.3299	1.2
Compcollege	-0.0066	-0.1079*	1.0
Hschorless	-0.1804	-2.5122	0.8
Ownhouse	-0.3342	-4.9219	0.7
Yrsdriving	-0.0161	-3.2516	1.0
Fulltime	0.0582	0.7650*	1.1
Parttime	0.4217	4.0401	1.5
Hmaker	0.3046	2.7182	1.4
Student	0.7598	2.7009	2.1
Conserv	0.1854	3.3369	1.2
Lib	0.2306	3.5628	1.3
West	-0.1772	-2.4915	0.8
Midwest	0.3213	5.0366	1.4
Northeast	0.2409	3.6013	1.3
Singfamh	-0.3862	-3.6344	0.7
Apartment	-0.7566	-5.9845	0.5
White	-0.2687	-3.6846	0.8
Urban	-0.0536	-1.0360*	0.9
Lninc	-0.0543	-1.3180*	0.9
monthmiles	0.0171	4.3824	1.0

*Parameter is not significant at 90% confidence level
**Omitted variables are ones that set as base

From model A, individuals with following attributes would be more likely to be assigned into the BEV-oriented class:

- Having more days in a month driving more than 80 miles
- Owning a car currently
- Having a vehicle with conventional engine like gasoline or hybrid
- Being elder
- Being male
- Being married
- Having a higher degree of education
- Not owning a house
- Having fewer years driving
- Working as part-time, home maker or student
- Being very conservative or liberal, not independent
- Living in the Midwest or Northeast
- Living places other than single family house and apartment
- White
- Earning lower income

Table 6
Model B - Class membership model estimates (Class 1 is normalized to zero)

Variables	Coefficient	T-stat	Odds Ratio
Class 2 Membership Constant	-0.4701	-2.4596	0.6

Morethan2days80miles	0.2469	4.6293	1.3
Currgas	0.6933	6.6390	2.0
Below40	-0.1993	-3.7036	0.8
Male	0.1412	2.8735	1.2
Married	0.1758	3.4200	1.2
Fulltime	-0.1853	-3.3835	0.8
Hschorless	-0.1045	-1.7869	0.9
White	-0.2915	-4.1973	0.7
Conserv	0.1523	2.7969	1.2
Lib	0.1794	2.8275	1.2
Midwest	0.3038	5.4996	1.4
lninc	-0.0841	-2.1938	0.9
monthmiles	0.0189	4.9663	1.0

From model B, individuals with following attributes are more likely to be assigned into BEV-oriented class:

- Having more days in a month driving more than 80 miles
- Having a vehicle with gasoline engine
- Older than 40 years old
- Being male
- Being married
- Working not as a full-time worker
- Having higher level of education
- Being not white
- Being independent
- Living in Midwest
- Earning lower income

- Having higher monthly miles

The significant and negative sign of class 2 constant from both models indicates that when given no sociodemographic characteristics, people are less likely to be assigned into class 2, which is the BEV-oriented class.

As explained, model A involves more individual characteristics in the model and has a larger log likelihood. However, it might not be as a good model as model B because it has the possibility of overfitting. In fact, some results from model A are not expected. For example, model A suggests BEV-oriented people do not own a house and the place they live in is not a single family house or apartment. This might diminish the possibility for them to have an at-home charging facility which is critical for BEV. Results from Model B will be discussed in part 4.4.

4.3.3 Willingness to pay for vehicle features

One objective of this research is to learn people's attitudes and then inform automobile manufactures about the preferences of their potential customers.

Willingness to pay is a monetary measurement of people's attitudes toward the attributes of the alternatives. There are generally two ways of deriving willingness to pay from customers. One method is to directly ask for the willingness to pay in the survey (contingent valuation). Another method is to derive estimate of the marginal rate of substitution from random utility model.

Since willingness to pay is the amount of money an individual would spend to get one attribute marginally improved, it can also be interpreted as the marginal rate of substitution between that marginal improvement and money. In economics, the marginal rate of substitution is the rate at which a consumer is willing to give up one good in exchange for another good while maintaining the same level of utility. In our random utility model, utility and attributes of alternatives are assumed as continuous variables, so that the willingness to pay for the alternative's attribute K:

$$WTP(K) = \left|MRS(K, \mathrm{Price})\right| = \left|\frac{MU(K)}{MU(\mathrm{Price})}\right| = \left|\frac{\partial U / \partial K}{\partial U / \partial \mathrm{Price}}\right| \tag{11}$$

For charging time and network, the willingness to pay for each can be calculated as:

$$WTP(A) = \left|\frac{\beta(K)}{\beta(\mathrm{Price})}\right| \tag{12}$$

For driving range, the willingness to pay is based on the specific value of driving range of the alternative. We can first assume the driving range to be 100 miles for all models:

$$WTP(DrivingRange) = \left|\frac{\beta(Range)}{\beta(\mathrm{Price}) \times Range}\right| \tag{13}$$

Operating cost is also a monetary variable as price. The willingness to pay for operating cost is the amount of current payment people are willing to make for $1 saving in the future cost. In economics, the ratio between the estimated parameters of price and operating cost is subjective discount rate r[8] (Frederick, Loewenstein, & O'donoghue, 2002), which tells how people think about current investment compared to future cost. If r is larger, people value present cost higher than future cost.

Table 7 shows the subjective discount rate, the willingness to pay for driving range (base is 100 miles), charging time and network in each model.

Willingness to pay calculated from each model is very close to each other simply because of the close values of estimated parameters. We will just use model B in the following analysis because model B is a better fit as discussed before, also for the sake of convenience.

Table 7
Willingness to pay estimates and subjective discount rate estimates

	Model A PHEV-oriented Class	BEV-oriented Class	Model B PHEV-oriented Class	BEV-oriented Class
Willingness to Pay				
Driving Range* ($/mile)	40	68	39	68
Fueling/Charging Time ($/hour)	282	539	281	538
Network ($/%)	62	25**	62	23**
Subjective Discount Rate (%)	11	N.A.	12	N.A.

* The base value of driving range is 100 miles.
** Parameter is not significant at 90% confidence level.

[8] In the neoclassical theory of interest due to Irving Fisher, the interest rate determines the relative price of present and future consumption. Time preference, in conjunction with relative levels of present and future consumption, determines the marginal rate of substitution between present and future consumption. This marginal rate of substitution is the subjective discount rate.

People in the BEV-oriented class are willing to pay more for longer driving range and shorter charging time. From the class membership assignment analysis, this might be because they have more days traveling long distance so that they need vehicles to cover longer range and is faster to charge. Also it might be because they are more likely to have a gasoline car which suggests that they are used to longer driving range and shorter charging time. This finding is in line with the previous studies. They are not sensitive to the accessibility of recharging station because they pay more interest on driving range and charging time which decrease the possibility of charging at stations.

People in PHEV-oriented class has a subjective discount rate of 12%. Our respondents seem to care about more about future savings, even though 12% still is higher than market interest rates.

We would like to pay more attention here to the willingness to pay for driving range. As explained before, the willingness to pay derived from this model is actually a function of the base driving range. To better understand the nature of willingness to pay for driving range, we simulate it with the Krinsky-Robb approach (Krinsky & Robb, 1986):

β_{price} and $\beta_{\ln range}$ are asymptotically bivariate normal:

$$\begin{pmatrix} \beta_{price} \\ \beta_{\ln range} \end{pmatrix} \sim N\left(\begin{pmatrix} \beta_{price,est.} \\ \beta_{\ln range,est.} \end{pmatrix}, \begin{pmatrix} s.e._{\beta_{price,est.}}{}^{2} & \mathrm{cov}(\beta_{price,est.}, \beta_{\ln range,est.}) \\ \mathrm{cov}(\beta_{price,est.}, \beta_{\ln range,est.}) & s.e._{\beta_{\ln range,est.}}{}^{2} \end{pmatrix} \right)$$

For each class, we considered driving ranges between 20 miles and 250 miles, and simulated 10,000 pairs of $\begin{pmatrix} \beta_{price} \\ \beta_{\ln range} \end{pmatrix}$ for every selected value of driving range. We then derived the willingness to pay using Eq. 13. Then we obtained the 95% confidence interval for every value of driving range using the simulated values. Fig. 2 and Fig. 3 show the willingness to pay variation as a function of driving range.

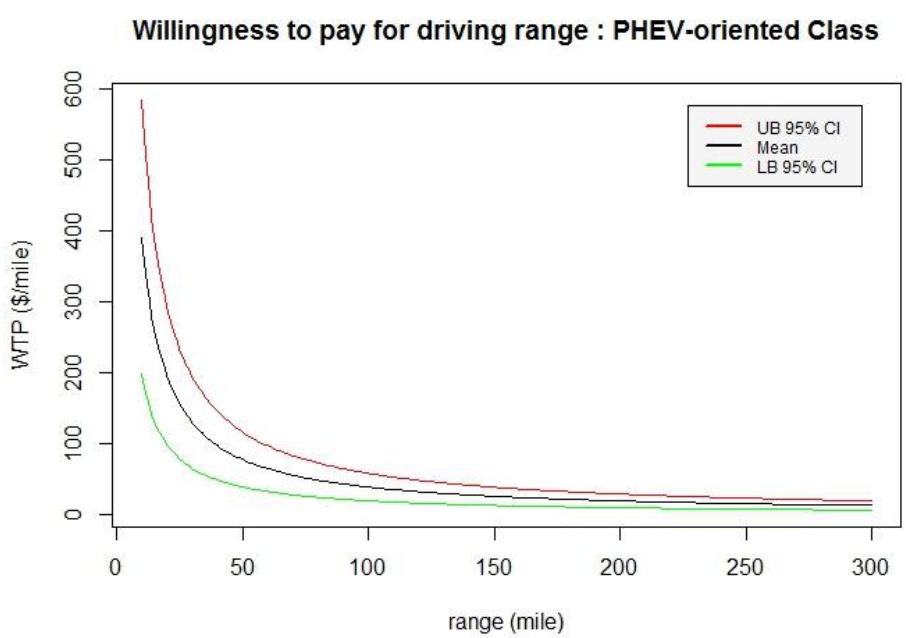


Fig.2 Willingness to pay simulation result for PHEV-oriented class

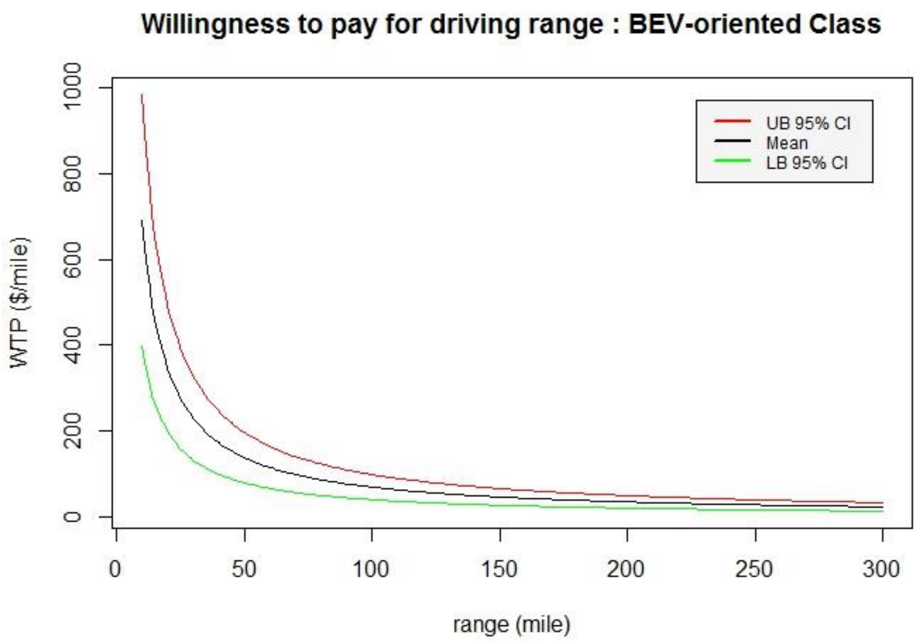


Fig.3 Willingness to pay simulation result for BEV-oriented class

From the two charts it is clear that people in the BEV-oriented class are willing to pay about 2 times more for driving range than people in the PHEV-oriented class as explained before. More importantly, the willingness to pay for range decreases as driving range increases, and so does the standard error of the estimate. This support the hypothesis that people tend to be less sensitive for the extra one mile as driving range goes up. This is also in accordance with the findings of Daziano R.A. (2013).

4.4 Summary of findings and comparison with early studies

From our model result, we have found that people are actually open to EVs, they can be grouped into PHEV-oriented or BEV-oriented classes. This is the natural result from the rising interest in EV and its advances over the years.

For sociodemographic characteristics, we found that people who are older (above 40 years old), having higher degree, and male are more BEV-oriented. This is in line with the findings from Nixon and Saphores (2011). For income effects, we found that even though BEVs are more expensive, people with higher household's income do not prefer BEVs even they are more possible to afford BEVs. This is in accordance with results from Bunch et al. (1993), who also found that higher-income households indicated a preference for gasoline vehicles over alternative-fuel vehicles. Besides, people who currently have gasoline vehicles, who are not fulltime workers, who are not white, who are more independent, and who travel longer distance or have more days in a month which travels more than 80 miles would prefer BEVs over PHEVs, which are kind of unexpected. One possible interpretation is people in BEV-oriented class are BEV enthusiasts and if BEVs are improved, their preference toward BEVs would be enhanced, for example, BEV enthusiasts are willing to pay more for driving range because they drive longer distance. Midwest is the location of many BEV manufacturing plants, this might be the incentive for people there to be more open to BEV, but not necessarily have one yet. Household number of vehicles is not significant, which is unexpected. But this might be because all the participant in our survey had at least one vehicle in household. There are few studies which covered these features so we cannot make valid comparison. Since discrete models are data sensitive, more detailed results from our model might result from the data we used.

We confirmed that driving range, charging time, and accessibility to charging infrastructure remain to be the main concerns when people considering EVs. The average willingness to pay regarding driving range from our model is from $40 to $70, on the 100 miles base. This range of value is close to the average willingness to pay from Beggs and Cardell (1980), Tompkins et al. (1998), and Hidrue et al. (2011) who also used U.S. nationwide survey data. The average values of willingness to pay regarding driving range from studies based on California survey data are higher. More importantly, the willingness to pay per mile decreases at higher driving range, which is expected and is in line with studies by Daziano (2013). BEV-oriented people are willing to pay more for driving range and charging time than PHEV-oriented people, they are more likely to be BEV enthusiasts and drive longer distances.

So far, model results have shown consumers' rising interest toward EV which is a good trend for the auto market. In this model, people can be either PHEV-oriented or BEV-oriented depending on their sociodemographic characteristics. Results has shown that there is opportunity for BEV to target consumers with particular attributes. For future improvement in EV options, driving range is still the main concern, especially for BEV.

The opportunity of economic benefits might differ for different EVs regarding marginal profit which leads to the following study of marginal manufacturing cost and consumers' willingness to pay.

Chapter 5 Study on current BEVs

In the U.S. market, mass-produced EVs has entered the market as full performance passenger vehicles. Nissan entered the U.S. market with the LEAF five-door hatchback in December 2010. As the most popular all electric vehicle in the U.S. market, 2016 year model of Nissan LEAF with a 24 kWh battery has a driving range of 84 miles as proved by the U.S. Environmental Protection Agency (EPA). Other makers such as Ford, Chevrolet and BMW are also producing BEVs in the U.S. market. More established ICEV makers are launching BEV models as an alternative and the entry-level BEVs are usually priced around $30,000. On the other hand, the U.S. based Tesla company is an all-new BEV-only auto manufacturer that entered the market as a high-end passenger vehicle producer. Unlike the Nissan LEAF, the Tesla model S is a luxury sedan that costs between $70,000 to $110,000, depending on the features and battery system. The EPA proved driving range of 2016 year model of Tesla S 70 is 230 miles, which is about 3 times that of the low-end BEVs and almost reaches parity with ICEVs. Starting from 2016, Tesla decided to enter the mass market as it unveiled a brand new model, the Tesla model 3, which is a lower-end version of Tesla S. Model 3 starts at $35,000 and still features an EPA proved driving range of 215 miles. Fig. 4 shows the MSRP for several BEVs on the current market.

These days EVs all have settled on lithium-ion (Li-ion) battery because this chemistry offers the most charge density per unit of weight in all the battery systems and technology breakthroughs keep increasing the charge density (Daziano, Electricity and hydrogen as alternative fuels, 2014). High charge density is beneficial because the curb weight of BEVs has a negative effect on the driving range. Inversely, the target driving range also influence the size of battery system.

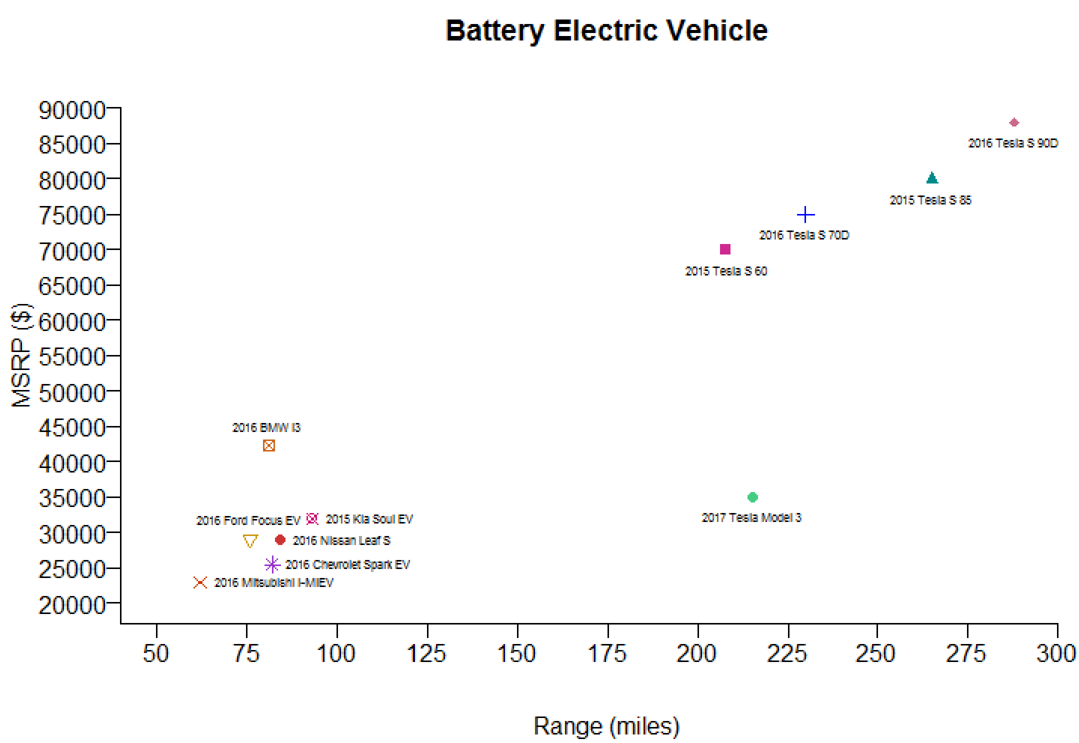


Fig.4 MSRP of current BEVs on the market

To find out how our results match current BEV models in the market, we used the 2016 Nissan Leaf and the 2016 Ford Focus EV for the low-end BEV, and the 2015 Tesla S 60 (no longer in production), 2016 Tesla S 70D and 2016 Tesla S 90D for the high-end BEV. Following the calculation methods raised up by Daziano R.A. (2014), we calculated the manufacturing cost for each vehicle and the marginal cost regarding driving range to compare with the willingness to pay we got from our model.

5.1 Manufacturing cost

We used an empirical model from Daziano R.A. (2014) in this section to calculate the cost. According to this model, we assumed that EV charge availability is constant down to the maximum depth of discharge $DD_{\max}$ (as a fraction of 100%). The simplified model also assumes a constant average energy intensity in terms of the energy required to marginally move the vehicle (μ measured in [Wh/kg-km]). If CD is the charge density, $W_{battery}$ is the mass of the batteries in kilograms, and $W_{vehicle}$ is the mass of remainder of the vehicle in kilograms (not including the battery), then range can be estimated as (range in km):

$$R = \frac{CD \cdot DD_{\max} \cdot W_{battery}}{\mu\left(W_{vehicle} + W_{battery}\right)} \tag{14}$$

Following the range model, and if the fixed cost of the vehicle is C_{fixed} (without the cost of the batteries) then the total cost, included the cost of the battery can be expressed as follows:

$$TC = C_{fixed} + \frac{R \cdot \mu \cdot W_{vehicle}}{\left(CD \cdot DD_{\max} - R \cdot \mu\right)} \times C_{battery} \tag{15}$$

where $C_{battery}$ is the unit cost of the batteries in dollars per kilogram.

Before using this equation to estimate battery requirements and total costs as a function of range, we collected related data for the models we listed above. Table 8 shows the properties of these five BEV models.

Table 8
Attributes of five BEVs

Model	Range (mile)	Range (km)	Curb Weight (lb)	Curb Weight (kg)
2016 Nissan Leaf S	84	135	3256	1477
2016 Ford Focus EV	76	122	3640	1651
2015 Tesla S 60	208	335	4323	1961
2016 Tesla S 70	230	370	4608	2090
2016 Tesla S 90D	288	463	4824	2188

We assumed that all the vehicles have the same $\mu = 0.128$ [Wh/kg-km]. Weissler (2010) reported the energy density of Li-ion battery used by general BEVs is 140 Wh/kg. According to Dr. Menahem Anderman's Tesla Battery Report, the cells in Model S offer a specific energy of 233 Wh/kg due to the NCA chemistry and high-density electrodes. This is roughly 50% greater than the current industry standard, exemplified by the 140 Wh/kg. According to an article on BEV's battery cost by Ottaway (2014), in 2015, the battery value of vehicles except Tesla is 300 $/kWh, the battery value of Tesla is 260 $/kWh. We also assumed that the maximum depth of discharge is 80%. We get the estimated battery cost and manufacturing cost for the five BEV models as shown in Table 9.

Table 9
Estimated manufacturing cost of 5 BEVs

Model	MSRP ($)	Battery Cost ($)	Manufacturing Cost ($)	Profit Margin (Profit/MSRP, %)
2016 Nissan Leaf S	29,010	9,571	26,771	7.7
2016 Ford Focus EV	29,170	9,668	26,868	7.9
2015 Tesla S 60	69,900	27,328	52,628	24.7
2016 Tesla S 70D	75,000	33,571	59,871	20.0
2016 Tesla S 90D	88,000	42,174	68,474	22.2

According to market study and company summary, it's safe to estimate the profit margin of Nissan Leaf and Ford Focus EV to be around 7%-9%[9] and the profit margin of Tesla model S to be around 25%[10]. We assumed the fixed vehicle cost for general BEVs and Tesla BEVS to be $17,200 and $26,200. We got the estimated profit margins for Nissan Leaf and Ford Focus EV to be 7.7% and 7.9% which are within the expected range of 7%-9%. Tesla S 70D and 90D are estimated to have profit margins at 20.0% and 22.2%. The estimated markup for Tesla S60 is higher. This might be because the values for cost calculation are based on current battery properties which are far better than that when Tesla S 60 was produced and sold. The profit margins calculated for Model S are around 25%. The calculations here are based on our assumptions of the

[9] According to a report in Wall Street Journal, January 2013, Ford's average pretax profit in North America per vehicle sold is $2,500, which is assumed here to be the average profit of Ford Focus. http://blogs.wsj.com/corporate-intelligence/2013/01/29/fords-margins-its-all-about-the-trucks/
Also assume Nissan LEAF has a similar profit rate as Ford Focus.

[10] According to a report in The Motley Fool, Dec 2015, Tesla Model S currently boasts a gross profit margin of around 25%. Tesla CEO Elon Musk also said their goal is to steadily improve gross profit margin and hopefully exceed 30% on Model S with 18 months.
http://www.fool.com/investing/general/2015/12/01/tesla-motors-incs-path-to-profits.aspx

fixed manufacturing cost, which might cause a bias. We tried to minimize the gap between our cost assumption and real cost by comparing our calculated profit margins with the actual profit margins.

It is obvious that when considering making and selling one vehicle, higher end EVs like Tesla give higher profits to its producer. Lower end EVs like Nissan Leaf give lower profit but they have an advantage in pricing. Compared with the Ford Focus EV, the Nissan LEAF is cheaper, has lower curb weight and longer driving range, which might be the reason why it’s the most popular BEV in the US market.

5.2 Marginal cost and willingness to pay for driving range

Automobile manufacturers think about the opportunity of improving their current BEVs and making a higher profit. In our research, we wanted to compare the willingness to pay for driving range estimated by our discrete choice model with the marginal cost for driving range derived from the simplified empirical range model, for the five BEVs. If the willingness to pay is larger than the marginal cost, then there is potential profit by increasing the driving range, otherwise, the manufacturer may not consider improve the option.

The marginal cost can be derived from Eq.14 as follows:

$$MC = \frac{CD \cdot DD_{\max} \cdot \mu \cdot W_{vehicle} \cdot C_{battery}}{\left(CD \cdot DD_{\max} - R \cdot \mu\right)^2} \tag{16}$$

For each BEV model, we simulated the willingness to pay and marginal cost regarding range using the same cost values as before. Table 10 shows the estimated willingness to pay for driving range for each BEV from both classes and the estimated marginal manufacturing cost for each BEV. Note that the mean and selected quantiles of willingness to pay are all shown as below. Note that the battery cost for low-end BEV (e.g. Nissan Leaf) is 300 $/kWh, the battery cost for high-end BEV (e.g. Tesla) is 260 $/kWh.

Fig. 5 shows the boxplot of the willingness to pay for driving range for the five BEVs. Note that low-end BEVs are associated with a higher willingness to pay for driving range. People in the BEV-oriented class are willing to pay more than people in the PHEV-oriented class. This might be because they are prone to drive longer distances as observed in our membership model result.

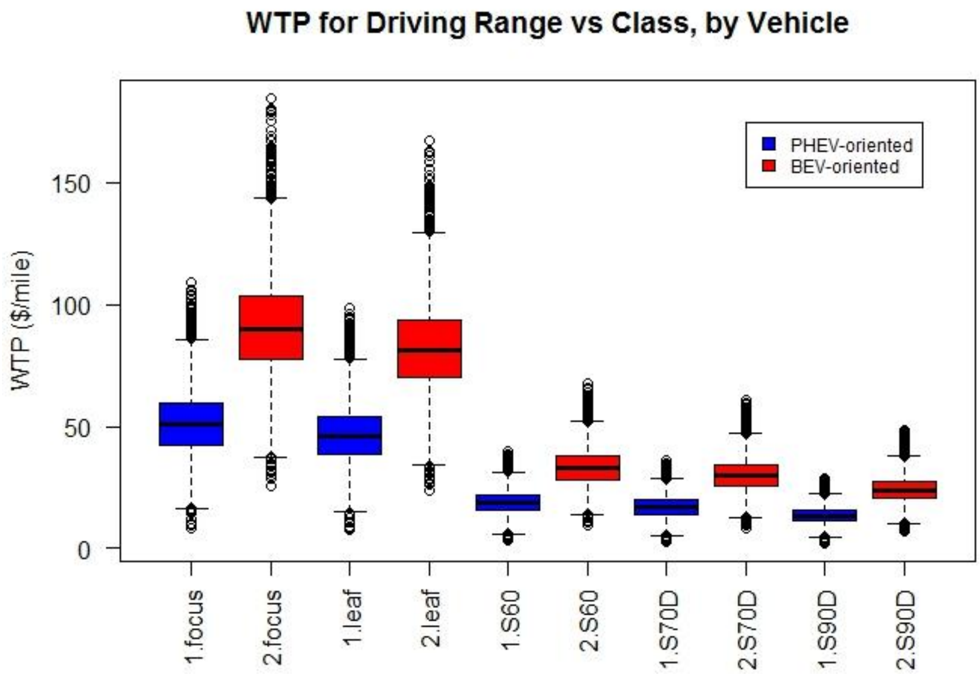


Fig. 5 Willingness to pay for 5 vehicles

Table 10
Mean and selected quantiles of the willingness to pay estimates for 5 vehicles

Quant.	Willingness to Pay ($/mile) PHEV-oriented Class	BEV-oriented Class	Marginal Cost ($/mile)
	2016 Nissan LEAF (84 miles)		
Mean	46	82	
2.5%	25	50	
25%	38	70	84
75%	54	94	
97.5%	71	119	
	2016 Ford Focus EV (76 miles)		
Mean	51	91	
2.5%	28	55	
25%	42	77	92
75%	60	104	
97.5%	78	132	
	2015 Tesla S 60 (208 miles)		
Mean	19	33	
2.5%	10	20	
25%	15	28	106
75%	22	38	
97.5%	29	48	
	2016 Tesla S 70D (230 miles)		
Mean	17	30	
2.5%	9	18	
25%	14	25	118
75%	20	34	
97.5%	26	43	
	2016 Tesla S 90D (288 miles)		
Mean	13	24	
2.5%	7	14	
25%	11	20	133
75%	16	27	
97.5%	21	35	

For the Nissan LEAF and the Ford Focus EV, the marginal cost of improving driving range is about the same as the estimated average willingness to pay from the BEV-oriented class. But the true value of the willingness to pay could be lower or higher if the 2.5% and 97.5% are taken as confidence interval bounds. On the other hand, the PHEV-oriented people have a willingness to pay that is consistently lower than marginal cost so that they might not be a good target regarding range improvement, compared to the BEV enthusiasts.

For all 3 Tesla models, the marginal cost regarding driving range is much higher than that of the LEAF and Ford Focus. However, people's willingness to pay are pretty low from both classes. This indicates that Tesla can barely make any higher profit by improving driving range. But this makes sense as the driving range is already very high and the marginal benefit from the extra one mile on utility should be relatively low as discussed before.

Table 11
Marginal costs regarding driving range at different battery costs

Vehicle	Marginal Cost ($/mile)			
	400 ($/kWh)	300 ($/kWh)	200 ($/kWh)	100 ($/kWh)
2016 Nissan Leaf S	112	84	56	28
2016 Ford Focus EV	123	92	61	31
2015 Tesla S 60	163	122	82	41
2016 Tesla S 70D	182	137	91	46
2016 Tesla S 90D	205	154	103	51

Note that due to the continuous advances in battery technology, the average battery cost has dropped down from 500 $/kWh to 300 $/kWh and it is expected to keep going down in the future. Because of this, we simulated the battery cost at 400 $/kWh, 300 $/kWh, 200 $/kWh and 100 $/kWh. Table 11 above lists all the marginal costs for the 5 vehicles regarding different battery costs. All the marginal costs come down with the battery cost decreasing. The effects on the Nissan LEAF and Ford Focus EV are more economically beneficial. When the cost comes down to 200 $/kWh, the marginal cost is close to the 2.5% quantile willingness to pay for BEV-oriented class which means about 97.5% estimated willingness to pay in BEV-oriented class are empirically higher than the marginal cost. Meanwhile, the marginal cost at 200 $/kWh is close to the 75% quantile willingness to pay for PHEV-oriented class which means about 25% estimated willingness to pay in PHEV-oriented are empirically higher than the marginal cost. This is already a great improvement compared with 300 $/kWh. When the marginal cost is 100 $/kWh, the proportion of estimated willingness to pay which are more than the marginal cost in BEV-oriented and PHEV-oriented class are about 100% and 97.5%. However, even when the battery cost comes down to 100 $/kWh, the marginal costs for Tesla models are still higher than the 97.5% quantiles of willingness to pay. Fig.5 and Fig.6 shows the marginal cost at different driving ranges by battery cost of Nissan Leaf and Tesla S 70D. Even though lowering battery cost gives more decrease in marginal cost of Tesla S 70D, its marginal cost is still very high compared with Nissan Leaf. Figures for the other 3 models are covered in Appendix C.

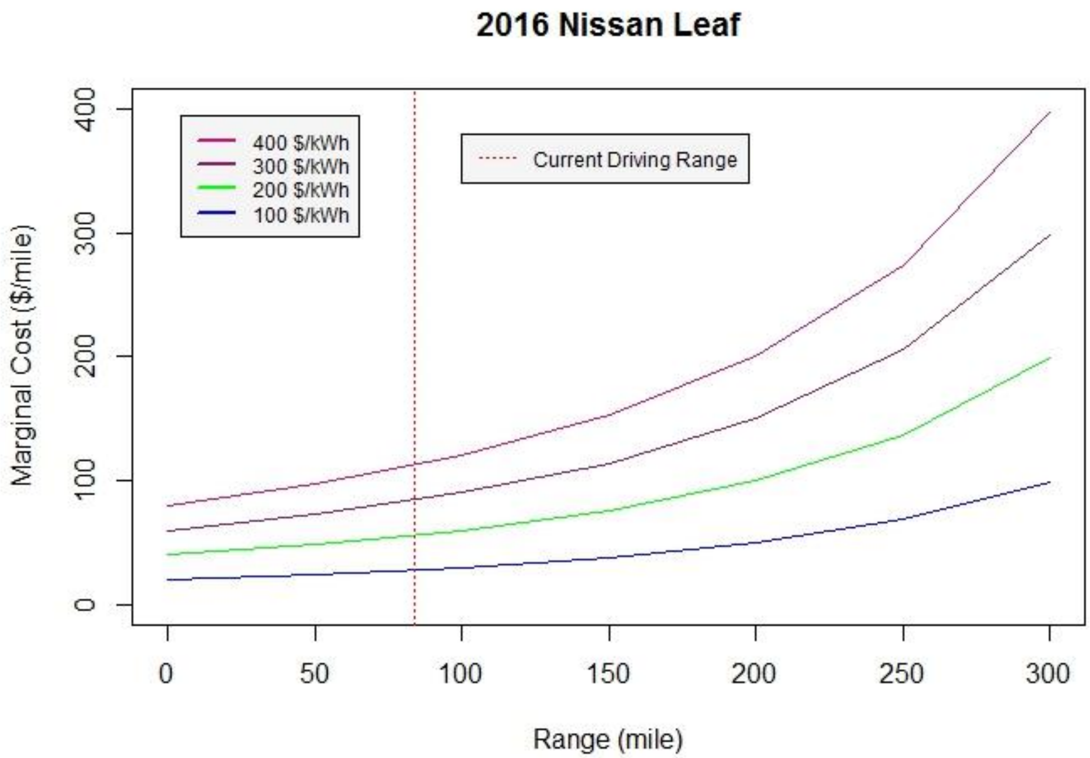


Fig. 6 Marginal cost for Nissan LEAF regarding driving range by battery cost

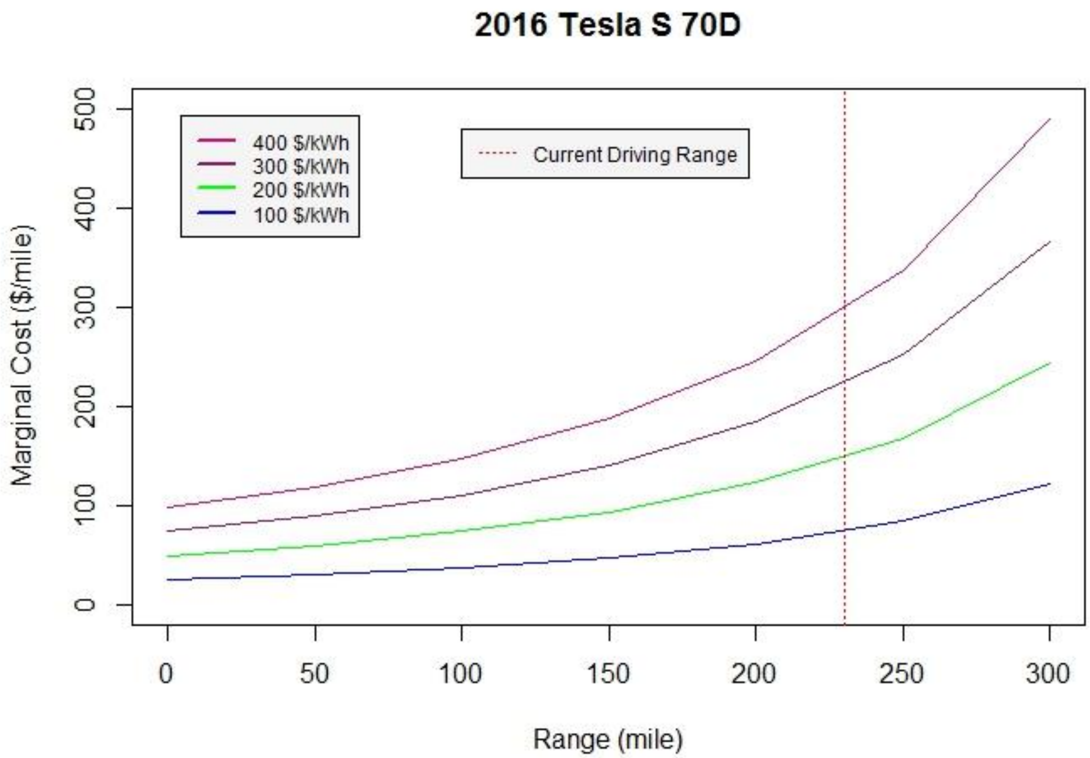


Fig.7 Marginal cost for Tesla S 70D regarding driving range by battery cost

We can conclude from our case study that for low-end BEV makers, increasing driving range can bring higher profit as well as appeal to more consumers, especially when lowering battery manufacturing cost. While for high-end BEV makers, improving driving range on the current base might not be a good strategy to make profit. However, the profit rate from making and selling one high-end BEV is much higher than a low-end BEV based on our cost assumption and references from profit reports. These findings are consistent with the competitive landscape on the auto market.

Chapter 6 Conclusion

This research added new insights into the demand for electric vehicles and confirms some earlier findings. We found that people in our sample were actually more open to BEVs and PHEVs than we expected, especially that current gasoline vehicle drivers have tendency to be BEV oriented when purchasing their next vehicle. We found person's propensity to be a BEV enthusiast increases with education, age, independence, traveling longer distance, having more free time, being married, living in Midwest. It also increases if a person is male and non-white. It's surprising that income has a negative effect on purchasing BEV which means people with lower income have tendency to buy BEV. This might be because both federal and some states provide compensation and also BEV is the most economical in operating cost. Besides, the number of vehicles a household owns is surprisingly not important either [at least in our sample]. But this might be because all the participants in the survey already have at least one vehicle in their households. Some results are unexpected and one possible interpretation is people in BEV-oriented class are BEV enthusiasts and if BEVs are improved, their preference toward BEVs would be enhanced, so as their purchase decisions.

Our analysis also confirmed similar findings of earlier studies. Range anxiety, long charging time and high purchase price remain as main obstacles for people to adopt EVs. For example, we found that people are willing to pay on average about $68 (95%

confidence interval of [40,98]) to get one mile improvement when the driving range is 100 miles, and about $280-$530 for one hour saving in charging time.

Given the expectation of diminishing marginal effects when the driving range increases, our model specified a logarithmic transformation of range. The average estimated willingness to pay for driving range for the 2016 Tesla S 70D (230 miles) is about 37% of that for 2016 Nissan LEAF (84 miles).

From our case study on the current BEVs on the market, the marginal manufacturing cost regarding improving driving range for low-end BEV is far less than high-end BEV, plus the willingness to pay regarding driving range for low-end BEV is much higher. We also conducted the calculation and comparison between the estimated willingness to pay and marginal cost regarding driving range. It is proved that at current battery costs, there can be economic benefits from improving driving range for low-end BEV makers. And if automakers can lower the battery cost more, this benefit will be more assured. For high-end BEV makers like Tesla, making profit by increasing driving range will not be very promising.

One thing to keep in mind is that discrete choice modeling is highly sensitive to data. In this research, we use U.S. nationwide survey data which might also be the reason of some different findings compared to earlier studies which mainly used survey data in California.

In our research, people can either be PHEV or BEV enthusiasts. Actually, plug-in hybrid electric vehicles use power from internal combustion engine when electric system is depleted. To better tell the difference between vehicles in EV family, future research should focus on the comparison between plug-in hybrid and battery electric vehicles. Most researches so far did not preselect survey participants. To better understand people's preference toward ICEVs and EVs, future research can focus on the choice difference between households with no vehicle available and households with vehicles. Meanwhile, future research should combine stated and reveal preference data to compensate for the gap between stated intention and actual behavior.

Appendix A: survey summary by questions

Fig. A.8 – Fig. A.52 are the intuitive summary of sociodemographic characteristics results in the survey.

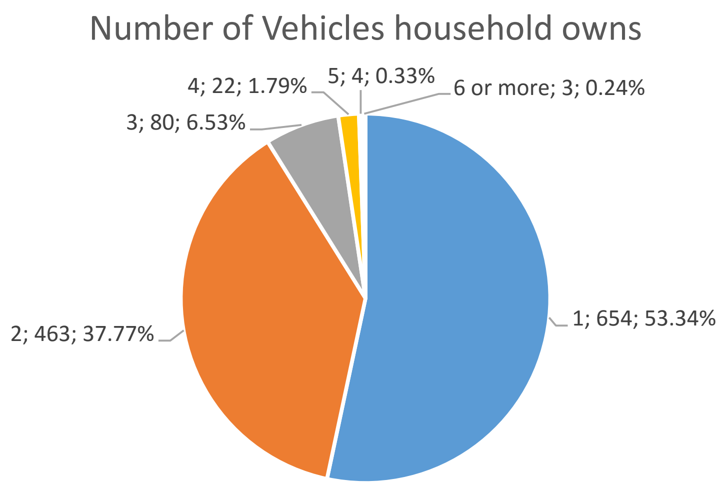


Fig. A.8 Number of vehicle household owns

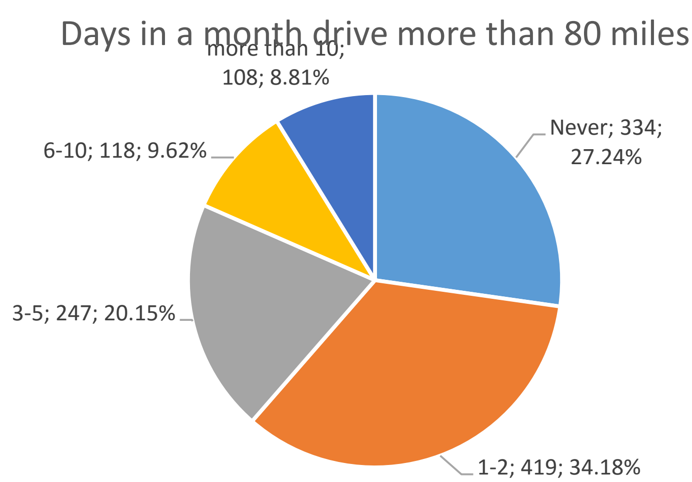


Fig. A.9 Days in a month drive more than 80 miles

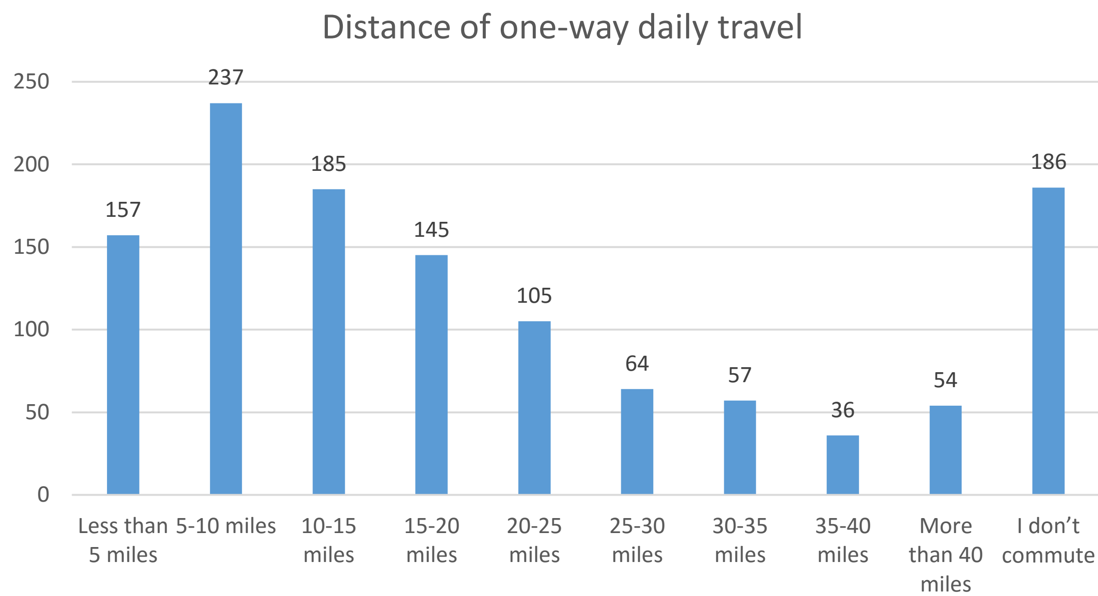


Fig. A.10 Distance of one-way daily travel

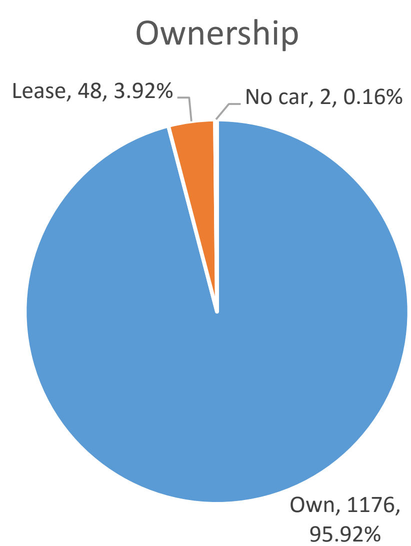


Fig. A.11 Vehicle ownership

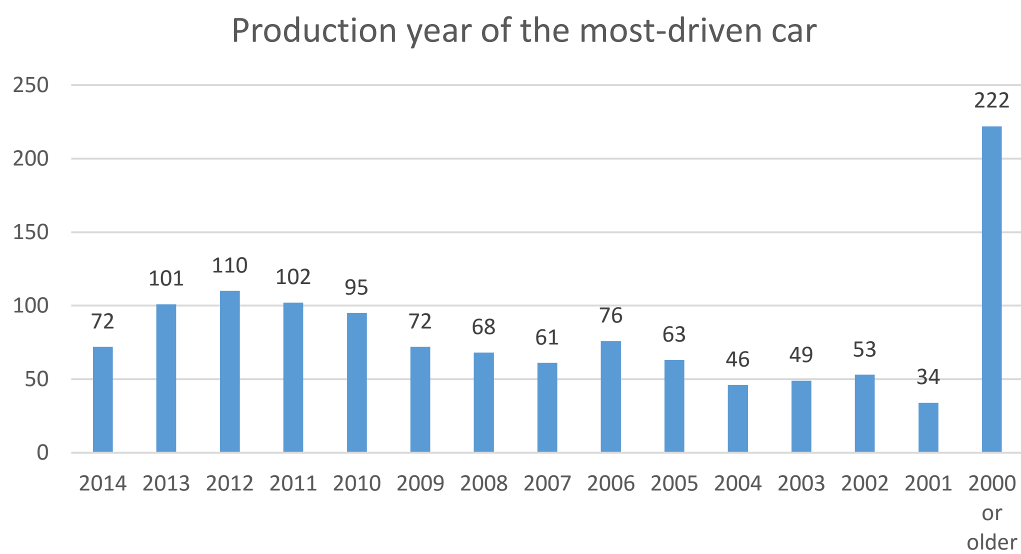


Fig. A.12 Production year of the most-driven car

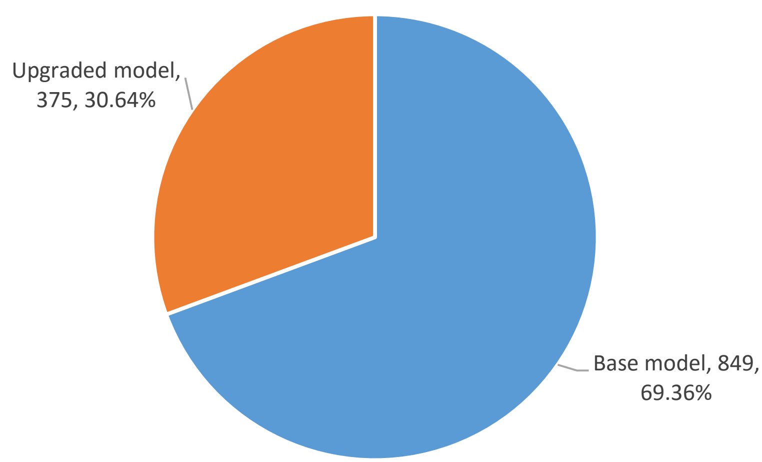


Fig. A.13 Upgraded model ownership

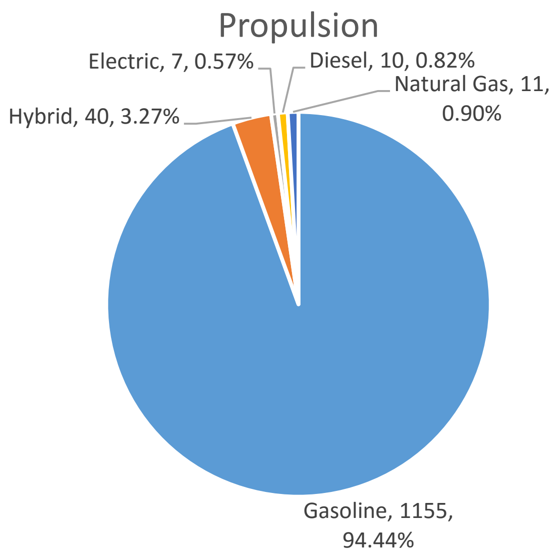


Fig. A.14 Propulsion of current vehicle

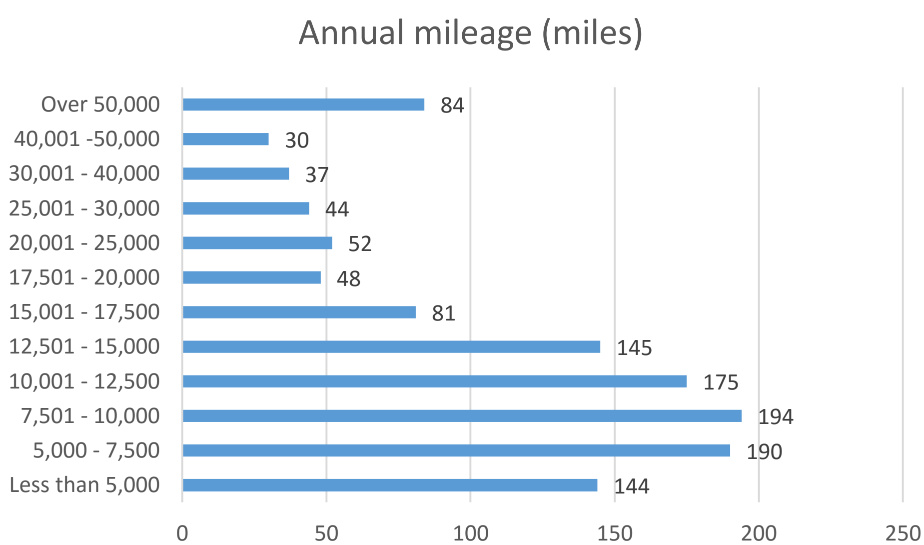


Fig. A.15 Annual mileage of current vehicle

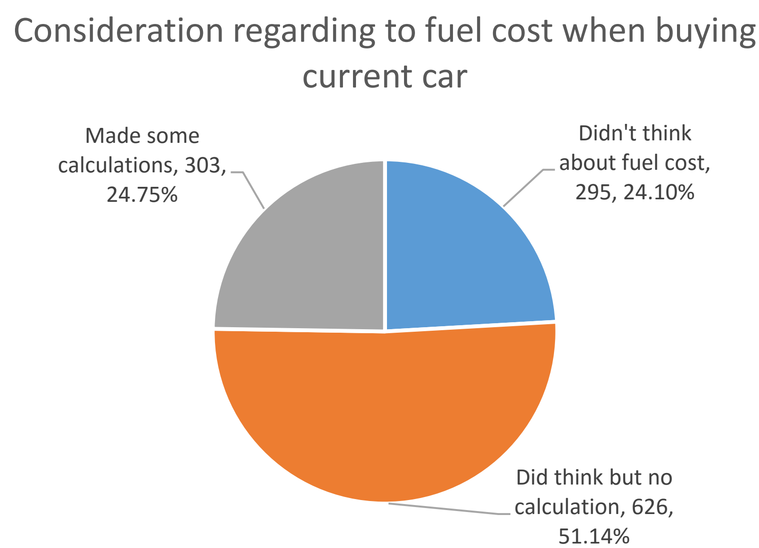


Fig. A.16 Consideration regarding fuel cost

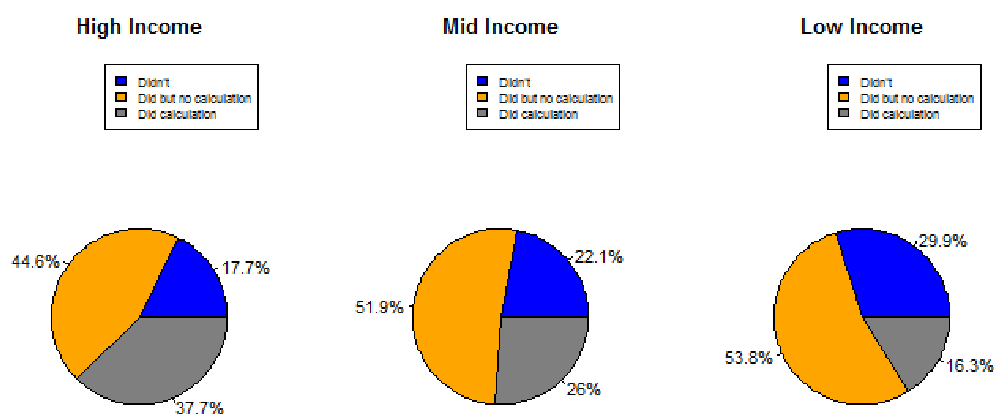


Fig. A.17 Consideration regarding fuel cost by income level

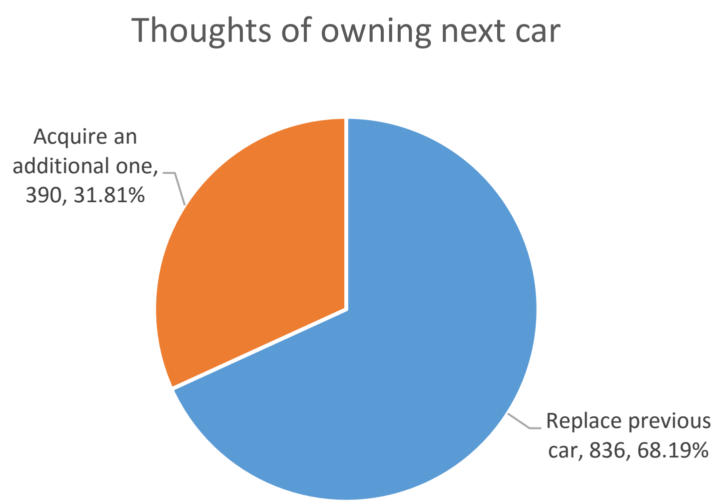


Fig. A.18 Purchase decision on next car

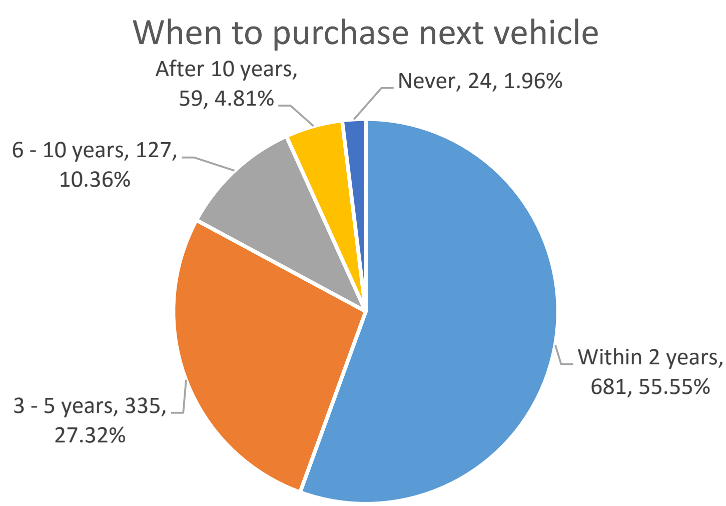


Fig. A.19 When to purchase next vehicle

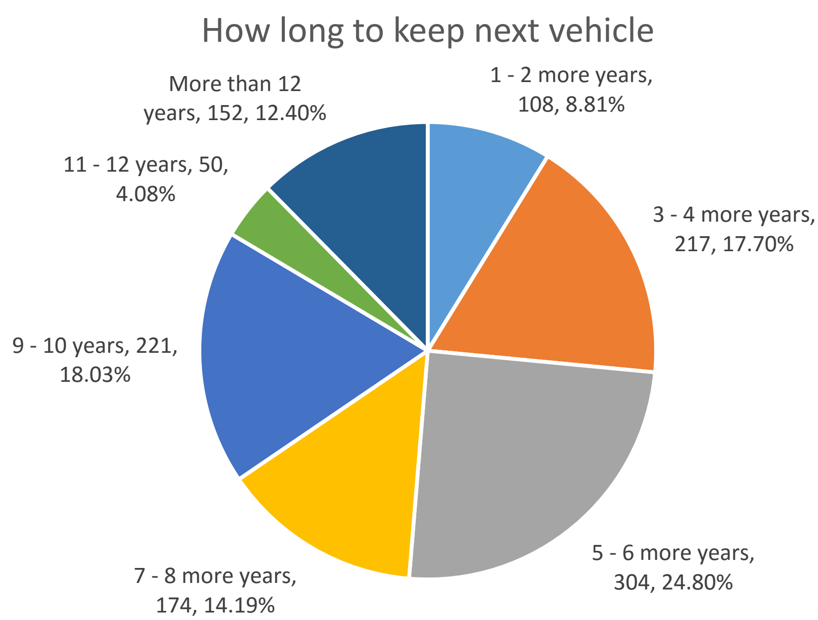


Fig. A.20 How long to keep next vehicle

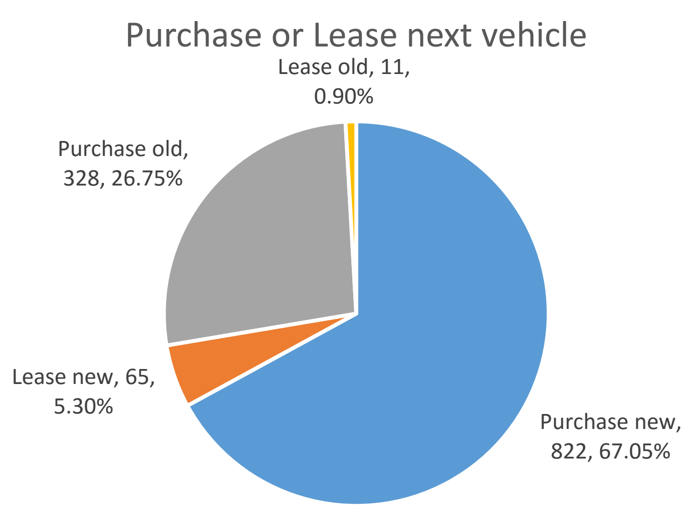


Fig. A.21 Purchasing method of next vehicle

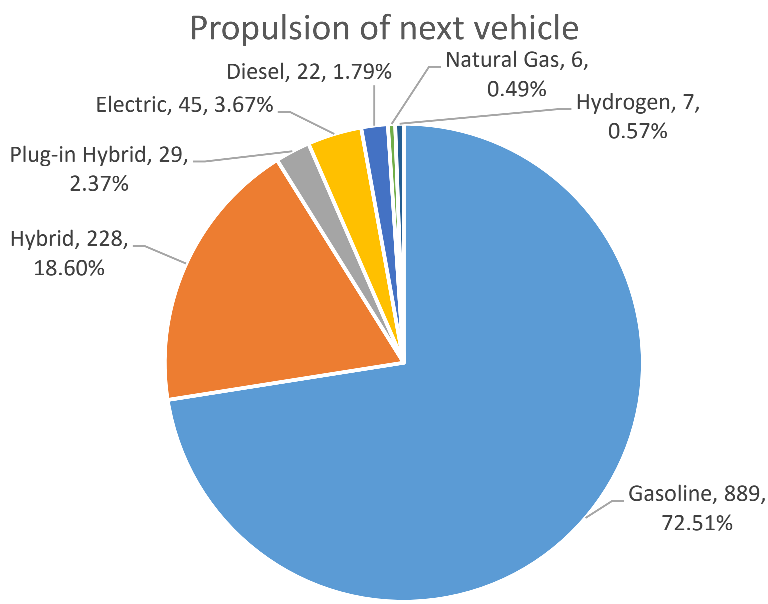
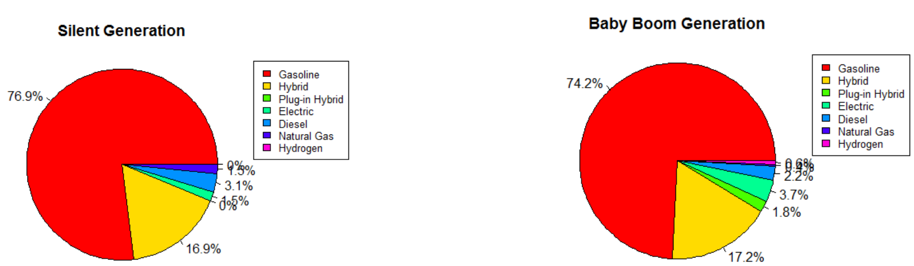


Fig. A.22 Propulsion of next vehicle



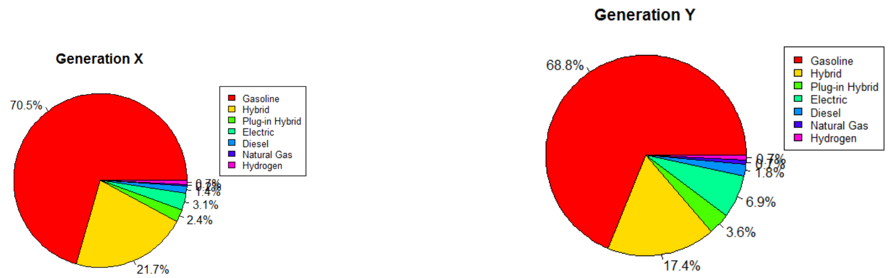


Fig. A.23 Propulsion of next vehicle by generations

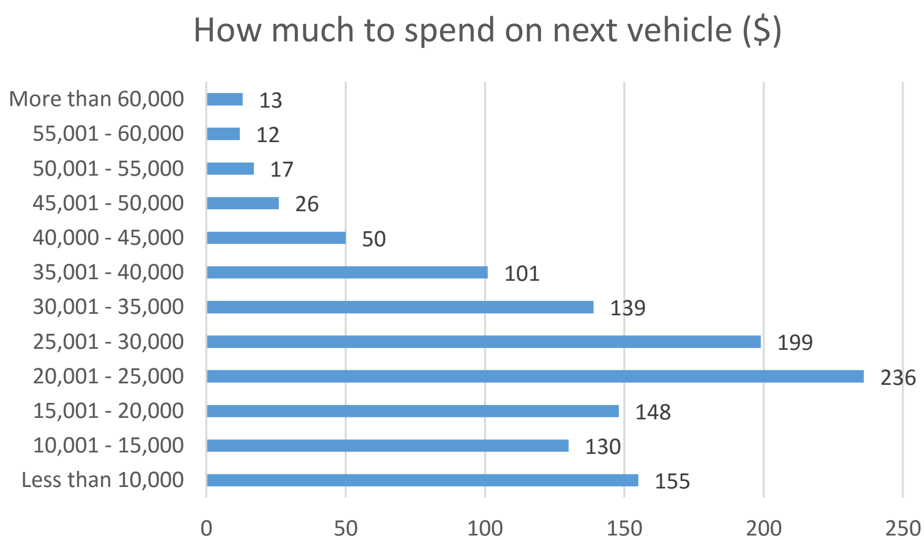


Fig. A.24 Budget plan for next vehicle

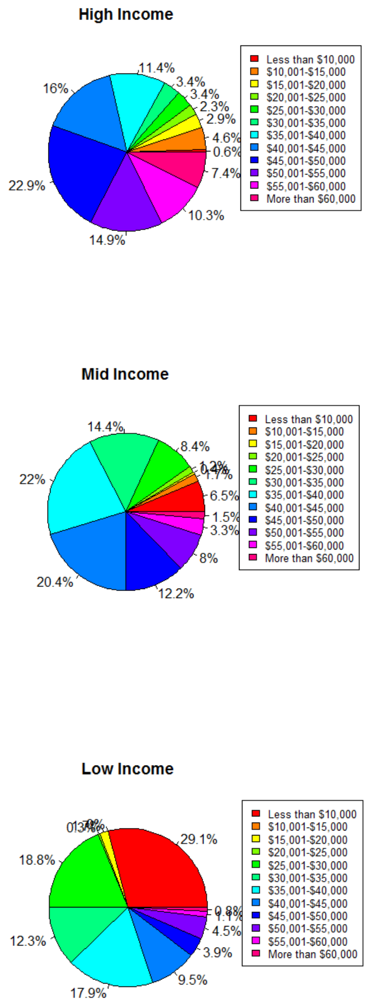


Fig. A.25 Budget plan for next vehicle by household income level

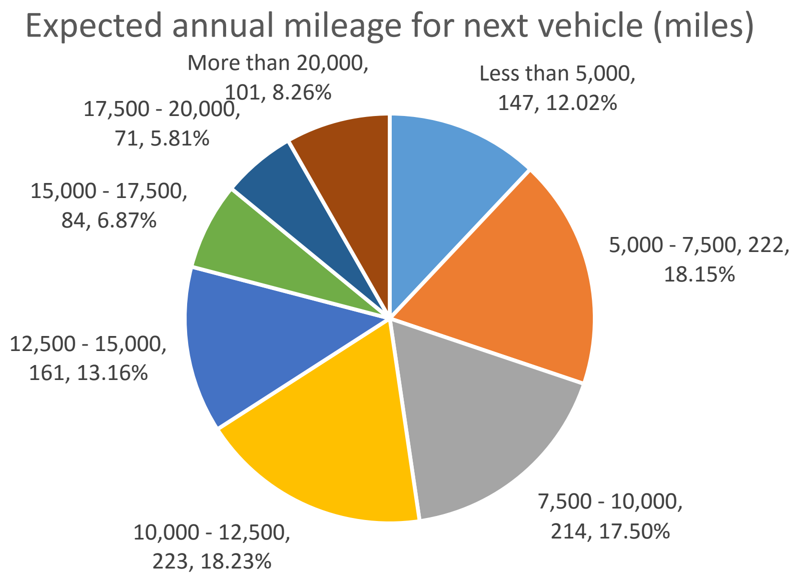


Fig. A.26 Expected annual mileage for next vehicle

Consider that you are about to buy a new car. Suppose an optimal engine was available, just as good in all respects as the engine you may consider buying, but more fuel efficient. If the optimal engine would save you $2,000 in fuel over 5 years, how much EXTRA would you be willing to spend for the vehicle?

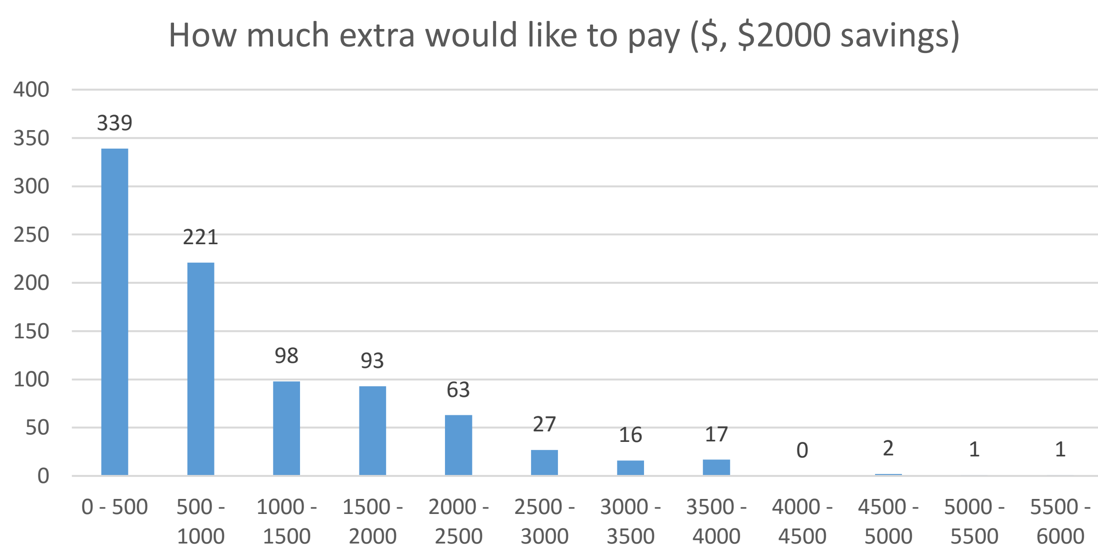


Fig. A.27 Willingness to pay for $2,000 savings in future fuel cost

Max	Min	Mean	Std
15,000	0	1053.416	1012.666

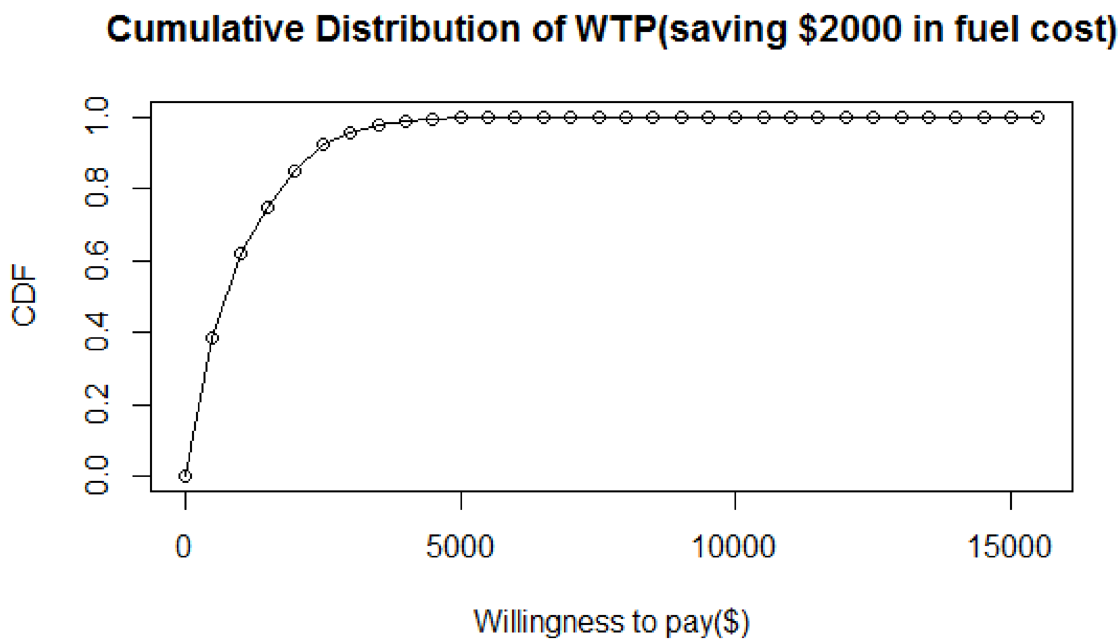


Fig. A.28 Cumulative distribution of WTP for $2,000 savings in fuel cost

If the optimal engine would save you $6,000 in fuel over 5 years, how much EXTRA would you be willing to spend for the vehicle?

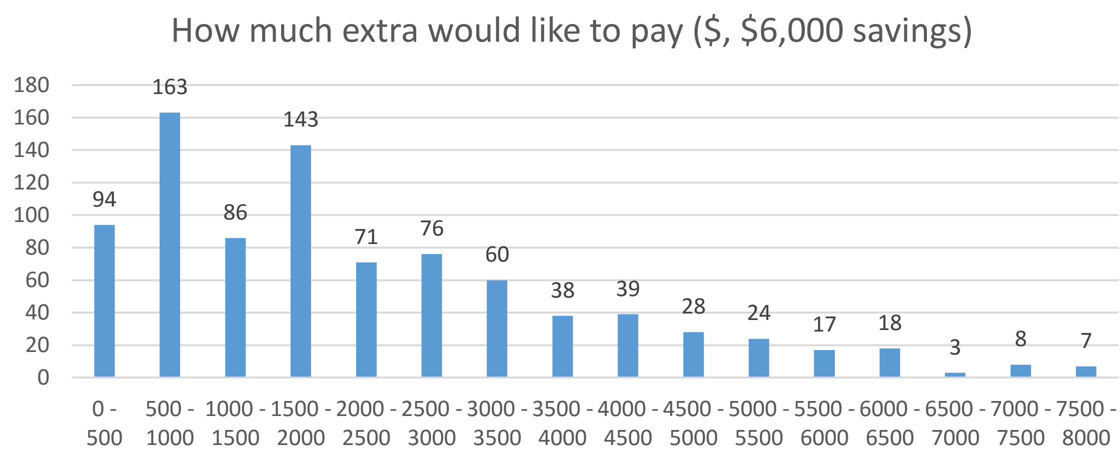


Fig. A.29 Willingness to pay for $6,000 savings in future fuel cost

Max	Min	Mean	Std
11,250	0	2269.745	1734.267

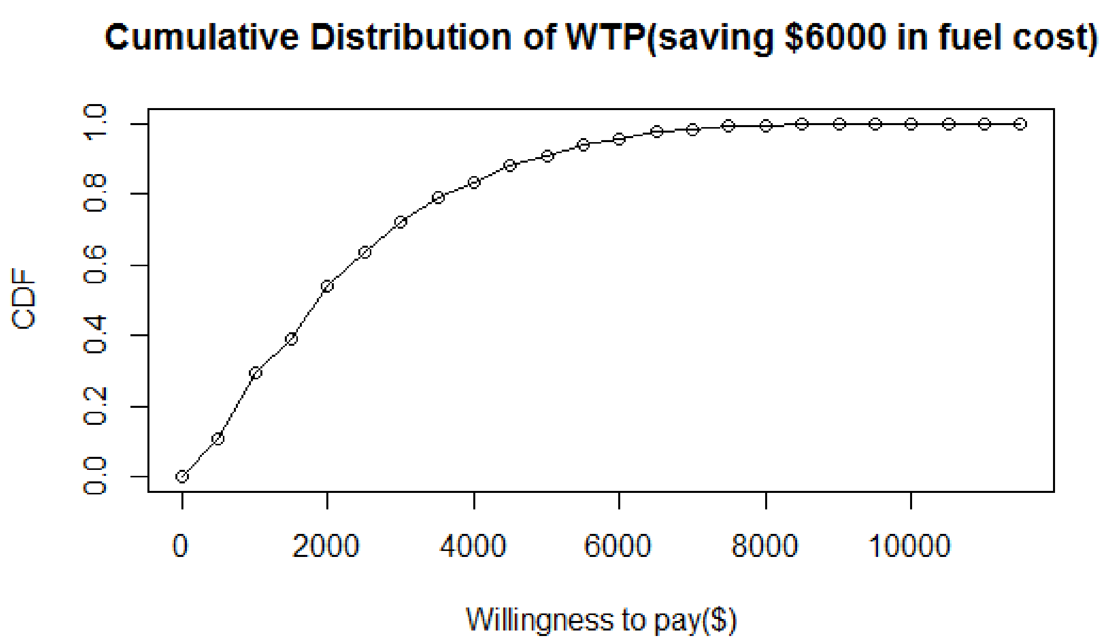


Fig. A.30 Cumulative distribution of WTP for $6,000 savings in fuel cost

If the optimal engine would save you $8,500 in fuel over 5 years, how much EXTRA would you be willing to spend for the vehicle?

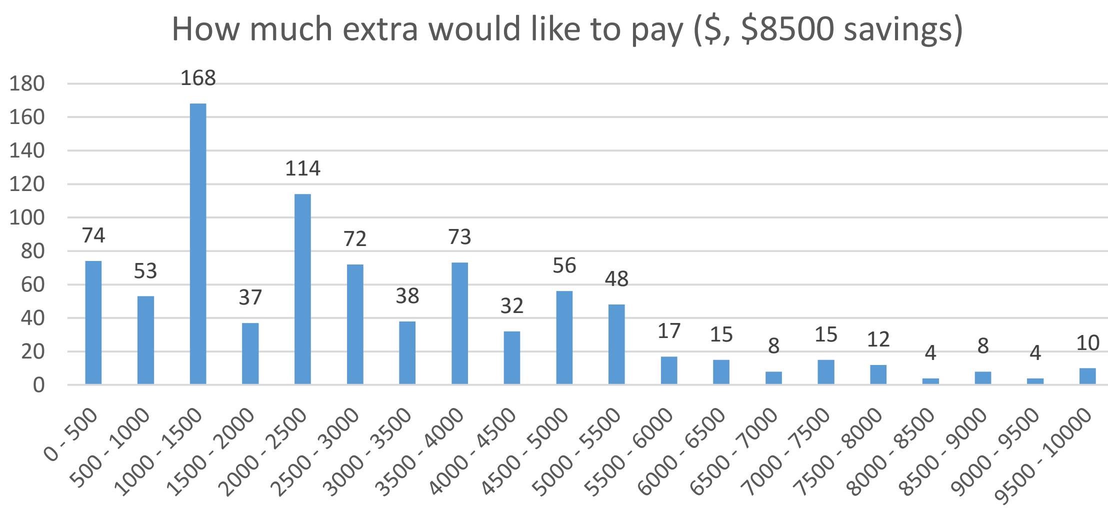


Fig. A.31 Willingness to pay for $8,500 savings in future fuel cost

Max	Min	Mean	Std
12101	0	2931.807	2178.629

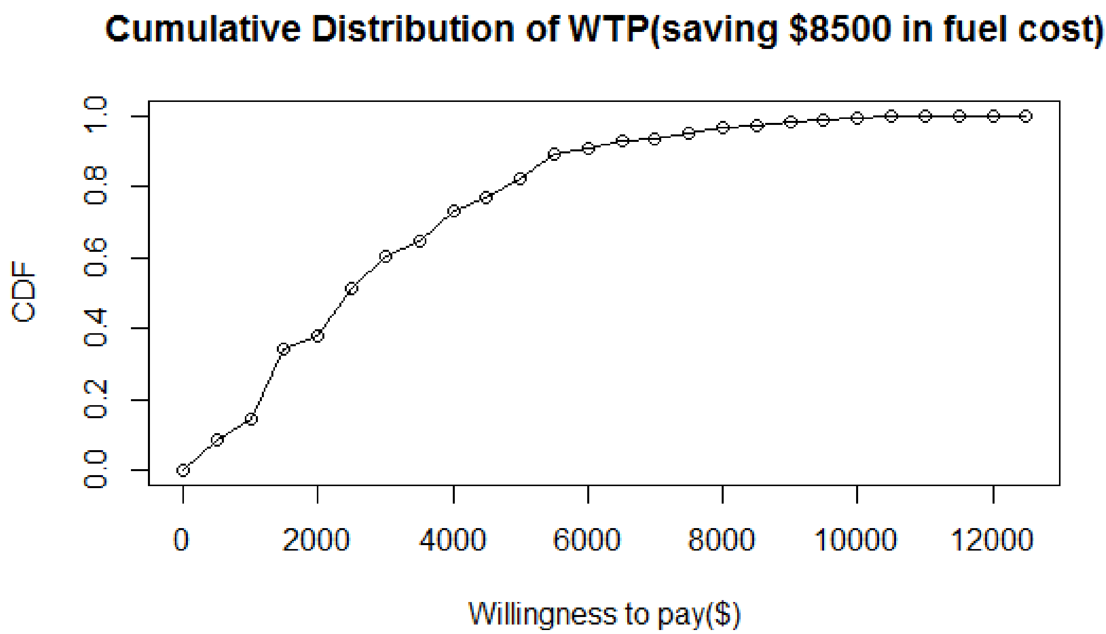


Fig. A.32 Cumulative distribution of WTP for $8,500 savings in fuel cost

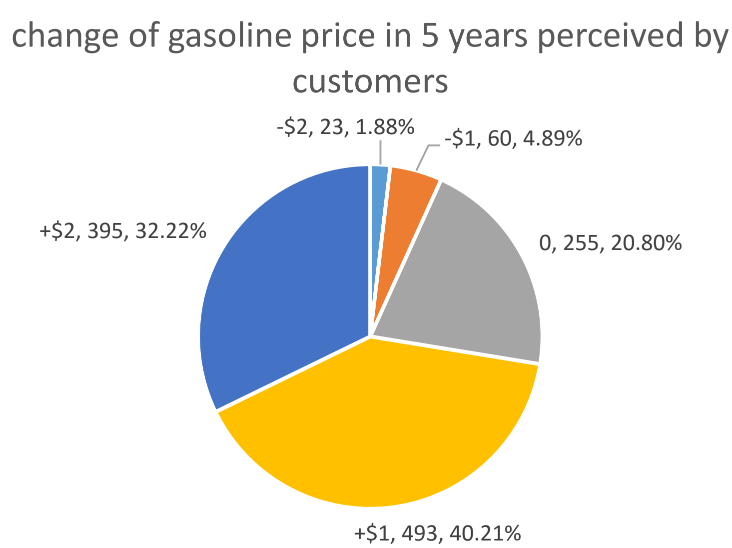


Fig. A.33 Predicted gasoline cost in 5 years by customers

Suppose you will be given a $5,000 award. What is your expected interest so that you are willing to receive it 2 months later.

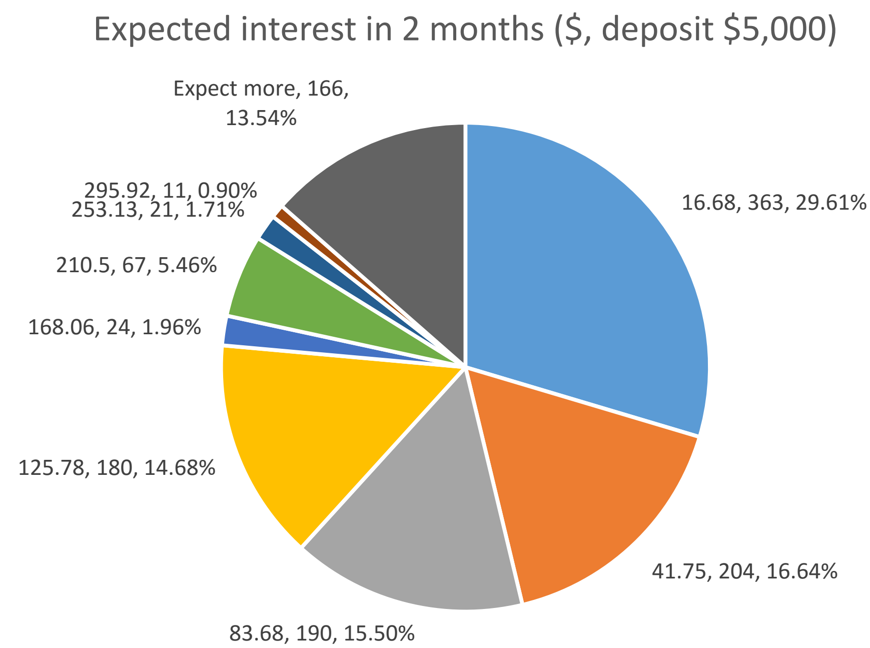


Fig. A.34 Expected interest in 2 months

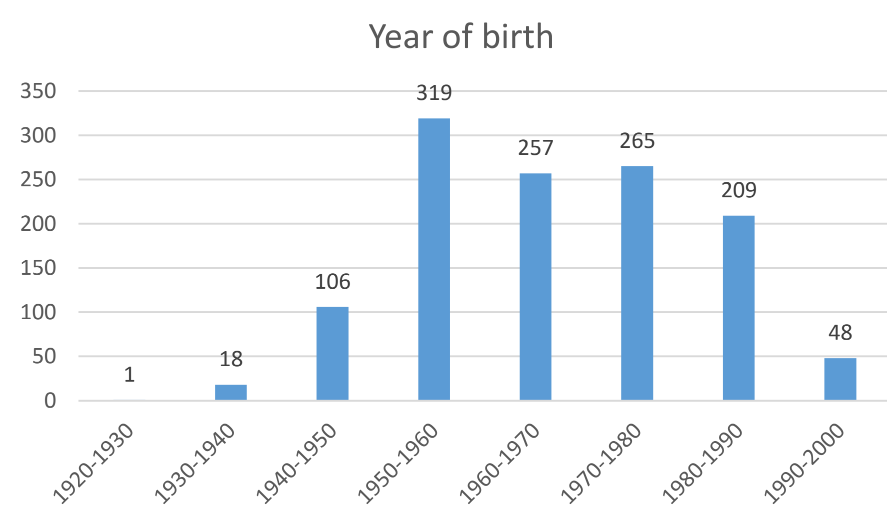


Fig. A.35 Year of birth

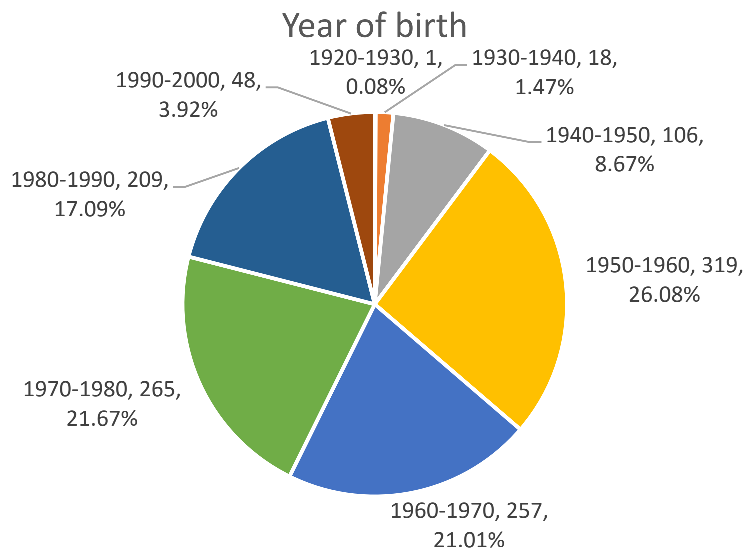


Fig. A.36 Year of birth

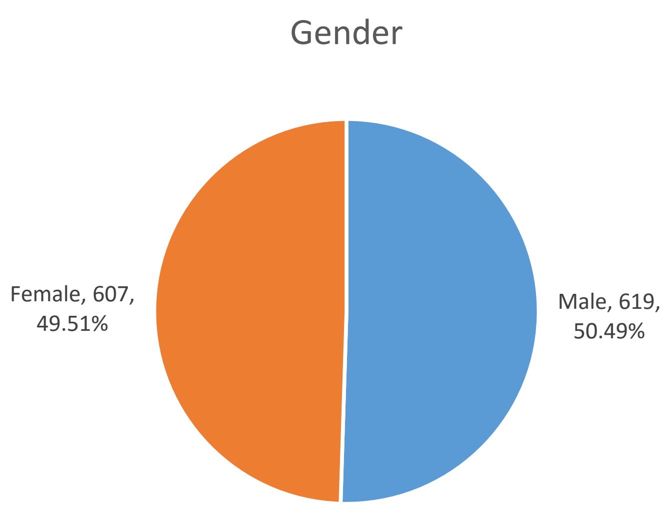


Fig A.37 Gender proportion

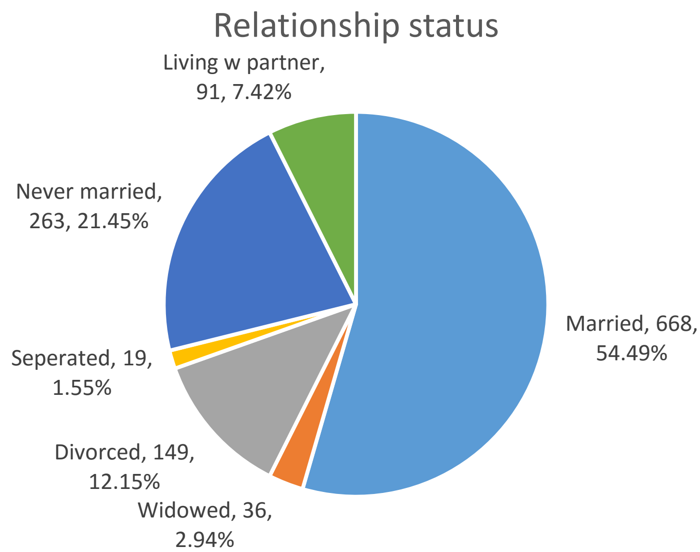


Fig. A.38 Relationship status

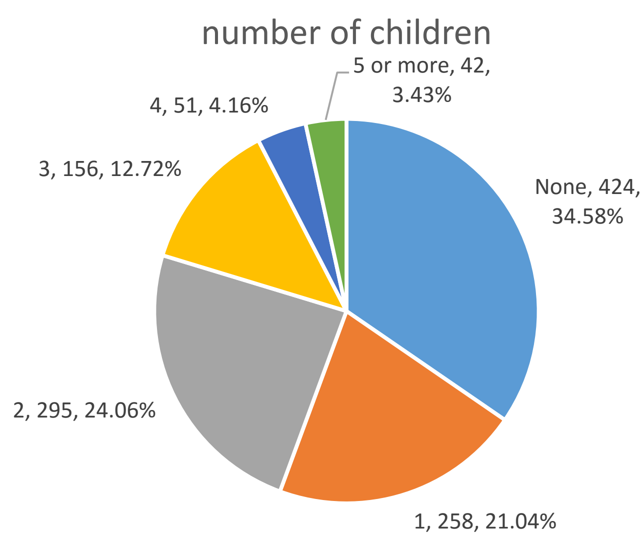


Fig. A.39 Number of children in household

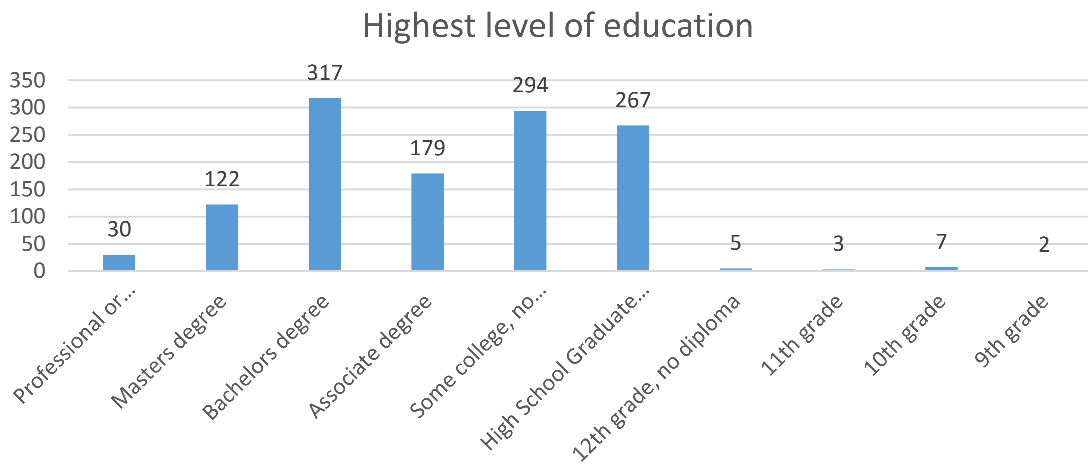


Fig. A.40 Highest level of education

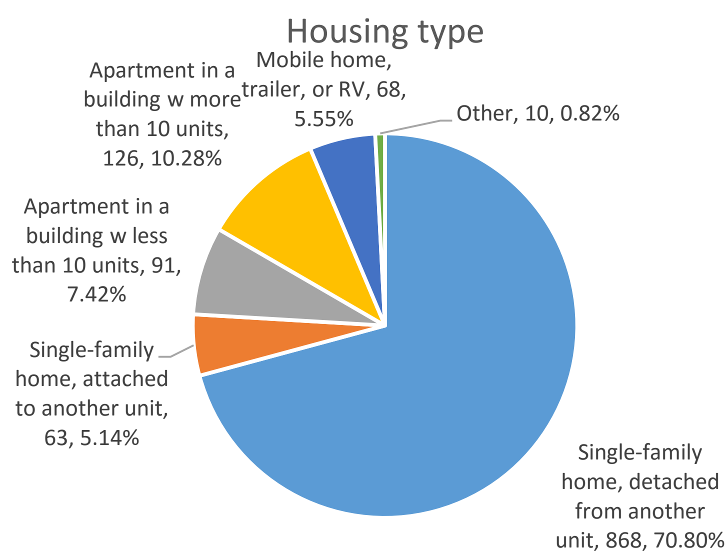


Fig. A.41 Housing type

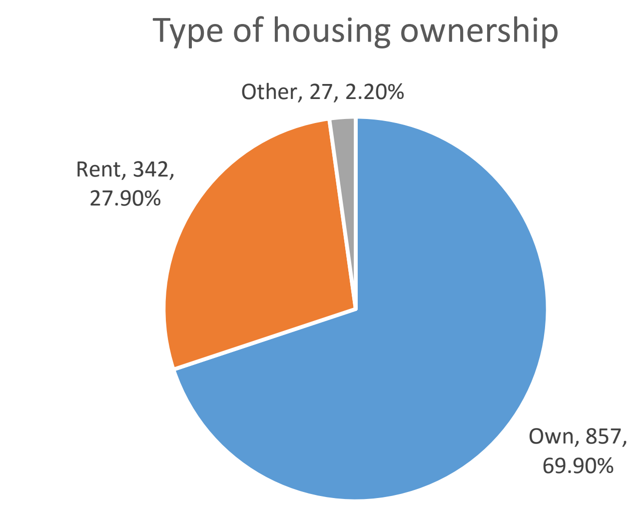


Fig. A.42 Type of housing ownership

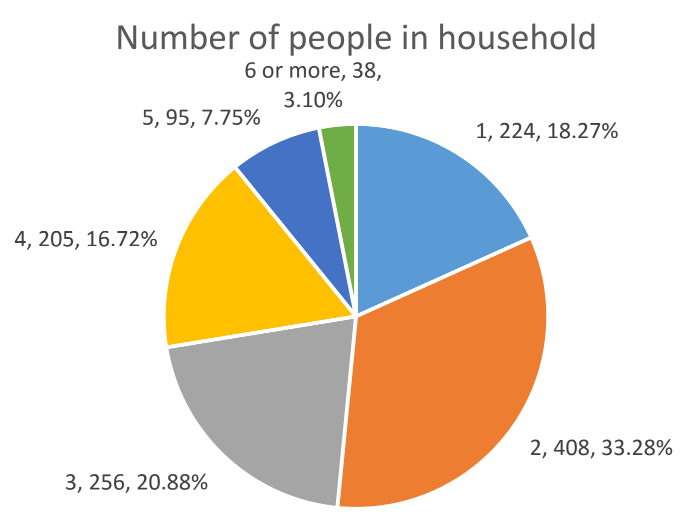


Fig. A.43 Number of individuals in household

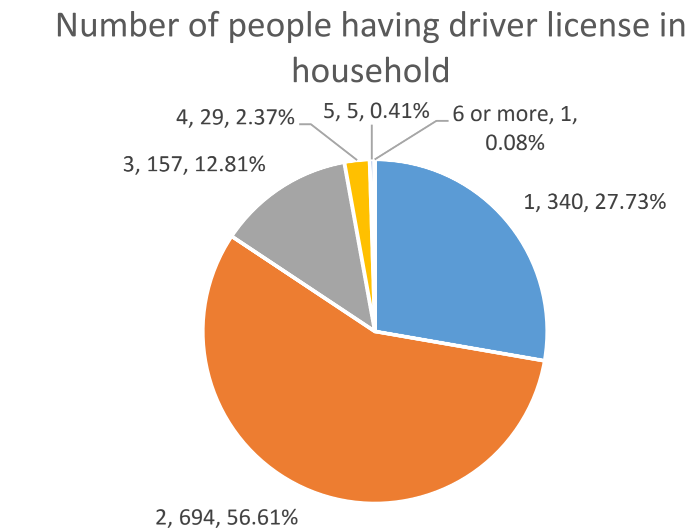


Fig. A.44 Number of driver’s licenses in household

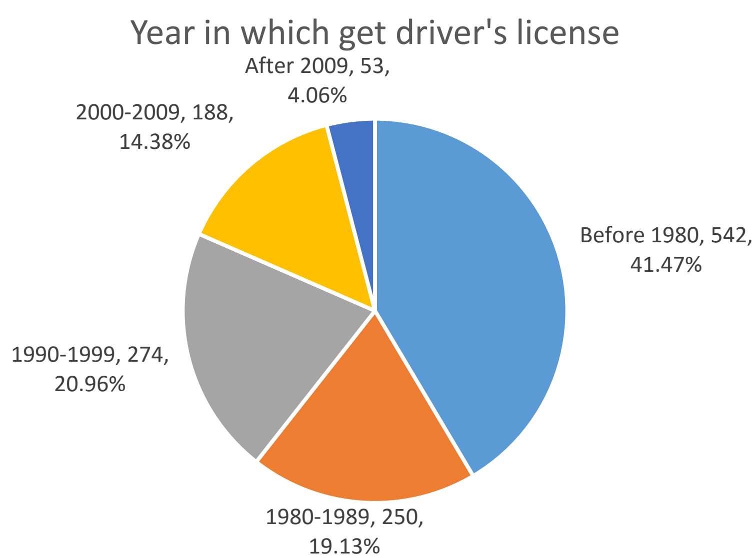


Fig. A.45 Year in which get driver’s license

When you drive with family or close friends, do you prefer to be the driver or do you prefer to be a passenger?

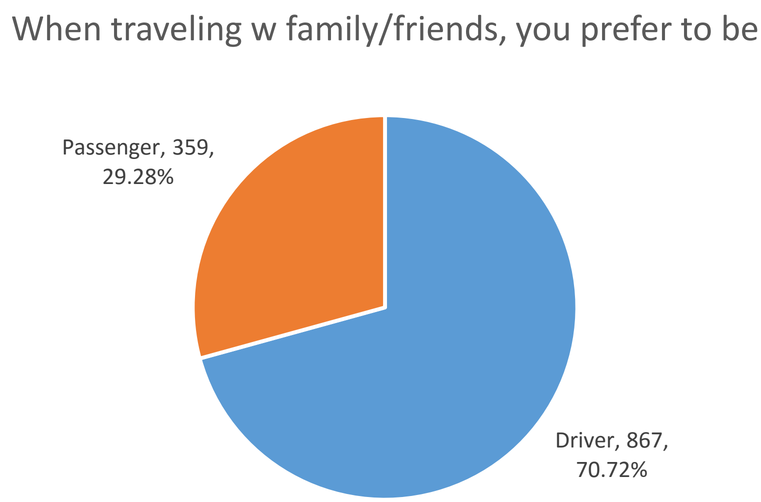


Fig. A.46 Preference of driving

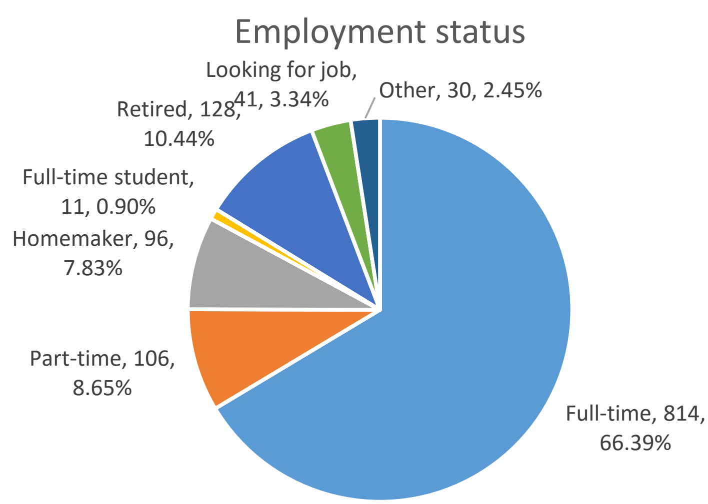


Fig. A.47 Employment status

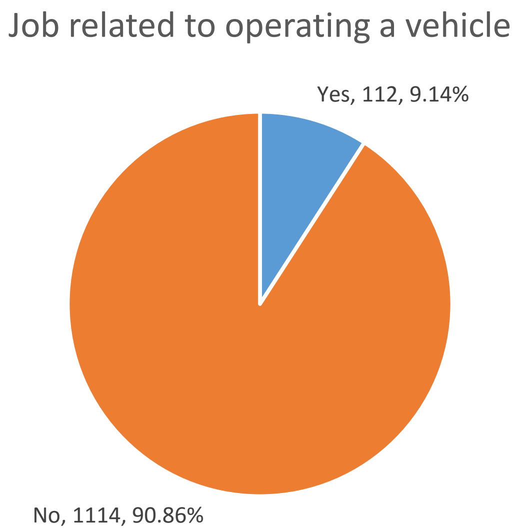


Fig. A.48 If job related to vehicle operating

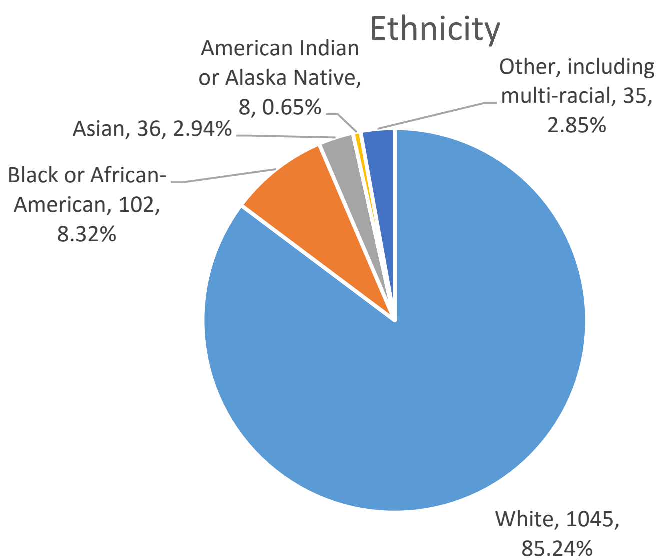


Fig. A.49 Self identification

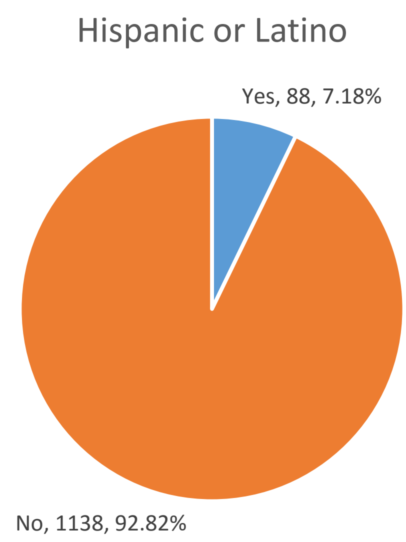


Fig. A.50 Latino or Hispanic

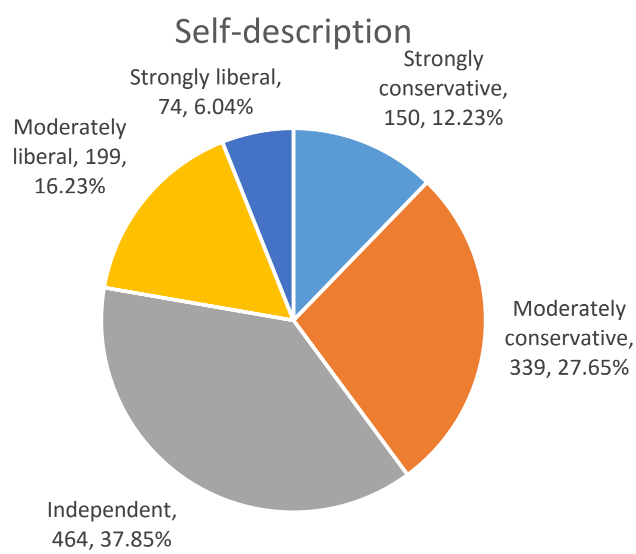


Fig. A.51 dependence level

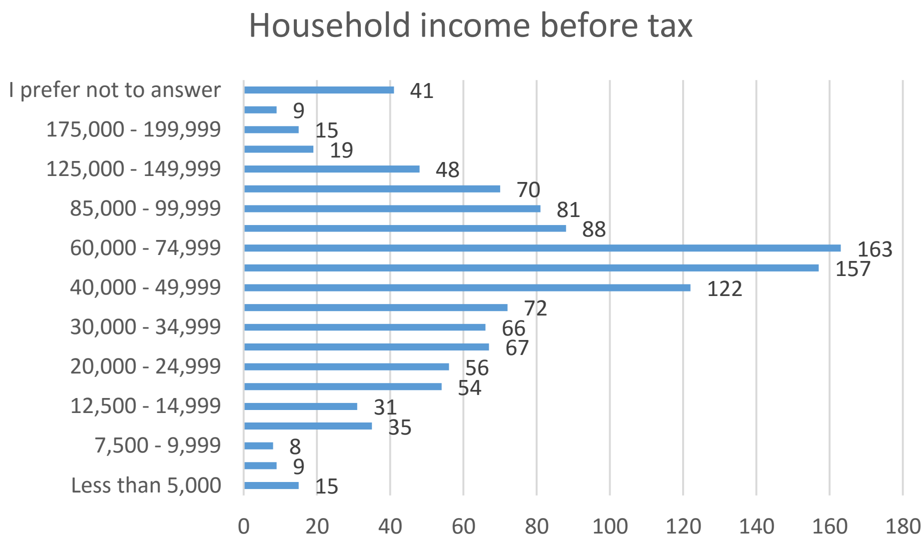


Fig. A.52 Household income before tax

Appendix B: Estimates from other models

Table B.13 – B.22 show the results from other models, including MNL, MIXL, LC, MMLM. We only list 10 typical models here because other models has similar results.

Multinomial Logit Model Estimates

Table B.13
MNL model with sociodemographic characteristics

	Estimate	Std. Error	t-value	Pr(>|t|)	
e:(intercept)	0.14981870	0.47633194	0.3145	0.753122	
h:(intercept)	-0.04228436	0.49956050	-0.0846	0.932545	
p:(intercept)	0.29923132	0.41187700	0.7265	0.467528	
price	-0.05307747	0.00301601	-17.5986	< 2.2e-16	***
ocost	-0.00159775	0.00211528	-0.7553	0.450046	
lnrange.e	0.28571587	0.06790212	4.2078	2.579e-05	***
lnrange.p	0.32897449	0.05429444	6.0591	1.369e-09	***
charget.e	-0.03045830	0.00648828	-4.6944	2.674e-06	***
network.e	0.36333711	0.12436202	2.9216	0.003482	**
network.p	0.36261238	0.13420946	2.7018	0.006896	**
e:days80miles	0.08079361	0.03016231	2.6786	0.007392	**
h:days80miles	0.07661130	0.04166464	1.8388	0.065950	.
p:days80miles	-0.00147090	0.03241814	-0.0454	0.963810	
e:currgas	-0.16282502	0.24178503	-0.6734	0.500674	
h:currgas	0.21648933	0.36409418	0.5946	0.552113	
p:currgas	-0.35138593	0.24908076	-1.4107	0.158324	
e:currhyb	-0.40783002	0.29482274	-1.3833	0.166571	
h:currhyb	0.22739941	0.43088790	0.5277	0.597676	
p:currhyb	-0.24154400	0.30289235	-0.7975	0.425185	
e:currelec	-0.76653667	0.52596594	-1.4574	0.145009	
h:currelec	0.40927285	0.67137797	0.6096	0.542126	
p:currelec	-0.51890468	0.54392519	-0.9540	0.340084	
e:age	0.00251996	0.00264354	0.9533	0.340463	
h:age	-0.00331635	0.00369110	-0.8985	0.368935	
p:age	-0.00029589	0.00281606	-0.1051	0.916319	
e:male	0.10138922	0.06608664	1.5342	0.124984	
h:male	0.14489780	0.09250730	1.5663	0.117269	
p:male	0.04427516	0.07046899	0.6283	0.529812	
e:married	0.12499879	0.06876313	1.8178	0.069092	.
h:married	0.18700663	0.09626241	1.9427	0.052055	.
p:married	-0.00970678	0.07321547	-0.1326	0.894527	
e:fulltime	-0.11932477	0.09625878	-1.2396	0.215114	
h:fulltime	-0.11034808	0.13507101	-0.8170	0.413949	
p:fulltime	-0.07784350	0.10247398	-0.7596	0.447469	
e:parttime	0.36567514	0.14235718	2.5687	0.010208	*
h:parttime	0.15738868	0.19630913	0.8017	0.422704	
p:parttime	0.21825377	0.15178333	1.4379	0.150454	
e:hmaker	0.04993981	0.14151067	0.3529	0.724160	
h:hmaker	-0.09923962	0.20100481	-0.4937	0.621506	
p:hmaker	-0.02506538	0.15150431	-0.1654	0.868595	
e:student	-0.05835485	0.32627356	-0.1789	0.858054	
h:student	-0.82199496	0.58889552	-1.3958	0.162767	
p:student	-0.33634878	0.35419467	-0.9496	0.342308	
e:white	0.07800866	0.16632435	0.4690	0.639059	

h:white	0.01572555	0.23141584	0.0680	0.945823	
p:white	0.21772009	0.17851996	1.2196	0.222623	
e:africam	0.24564924	0.19366912	1.2684	0.204656	
h:africam	-0.14586975	0.27704685	-0.5265	0.598529	
p:africam	0.17210644	0.20838955	0.8259	0.408868	
e:asian	0.50712191	0.26315010	1.9271	0.053965	.
h:asian	0.57962627	0.34405399	1.6847	0.092047	.
p:asian	0.50777999	0.27933103	1.8178	0.069088	.
e:conserv	-0.04108246	0.07240253	-0.5674	0.570431	
h:conserv	0.01720231	0.10018385	0.1717	0.863668	
p:conserv	-0.19775435	0.07738657	-2.5554	0.010606	*
e:lib	-0.02198853	0.08441501	-0.2605	0.794493	
h:lib	-0.12455041	0.12076104	-1.0314	0.302363	
p:lib	-0.07261177	0.08941880	-0.8120	0.416768	
e:west	0.06914978	0.09150754	0.7557	0.449845	
h:west	0.25744452	0.12657665	2.0339	0.041961	*
p:west	0.15057501	0.09616426	1.5658	0.117393	
e:midwest	0.26043251	0.08188437	3.1805	0.001470	**
h:midwest	0.27289428	0.11457427	2.3818	0.017228	*
p:midwest	0.04961058	0.08826821	0.5620	0.574086	
e:northeast	0.17028831	0.08544414	1.9930	0.046264	*
h:northeast	0.20523800	0.12056635	1.7023	0.088702	.
p:northeast	0.07244896	0.09119231	0.7945	0.426926	
e:monthmiles	0.00138189	0.02549848	0.0542	0.956780	
h:monthmiles	-0.00206263	0.01743959	-0.1183	0.905851	
p:monthmiles	0.00360749	0.02057947	0.1753	0.860847	
e:urban	0.01409304	0.06499631	0.2168	0.828342	
h:urban	-0.10505740	0.09162867	-1.1466	0.251565	
p:urban	0.11776785	0.06915044	1.7031	0.088555	.
e:lninc	-0.08173884	0.05027063	-1.6260	0.103955	
h:lninc	-0.13927927	0.06935426	-2.0082	0.044619	*
p:lninc	-0.05946158	0.05330370	-1.1155	0.264626	

Signif. codes: 0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1

Log-Likelihood: -11507
McFadden R^2: 0.030566
Likelihood ratio test : chisq = 725.64 (p.value = < 2.22e-16)

We implemented mixed logit models with different distributions for parameters.

Table B.14 shows the estimates from a simple MIXL model with no sociodemographic characteristics. All the parameters for alternative specific attributes were assumed to follow normal distributions. All the mean estimates has the right sign, but the stand deviations of parameters for price, operating cost, lnrange and network were too large.

Table B.14
MIXL with normally distributed taste parameters, no sociodemographic characteristics

	Estimate	Std. Error	z-value	Pr(>|z|)

e:(intercept)	0.23634881	0.22631156	1.0444	0.2963228	
h:(intercept)	-0.14720700	0.06937846	-2.1218	0.0338548	*
p:(intercept)	0.31074318	0.16946738	1.8336	0.0667066	.
price	-0.05849752	0.00327199	-17.8783	< 2.2e-16	***
ocost	-0.00382996	0.00079364	-4.8258	1.394e-06	***
lnrange	0.30633367	0.03900074	7.8546	3.997e-15	***
charget	-0.02697644	0.00592568	-4.5525	5.302e-06	***
network	0.43973515	0.12715253	3.4583	0.0005435	***
sd.price	0.03544472	0.00539241	6.5731	4.929e-11	***
sd.ocost	0.00491916	0.00067650	7.2715	3.557e-13	***
sd.lnrange	0.27487779	0.01330996	20.6520	< 2.2e-16	***
sd.charget	0.00583556	0.00948407	0.6153	0.5383557	
sd.network	0.02392315	0.21491912	0.1113	0.9113687	

Signif. codes: 0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1

Log Likelihood: -11188

Table B.15 shows the estimates of a MIXL model with sociodemographic characteristics. All the parameters for alternative specific attributes were assumed to follow normal distributions. The stand deviations for operating cost, lnrange, charging time and network were too large. Sociodemographic data did not have a good significance level.

Table B.15
MIXL with normal distributed taste parameters, with sociodemographic characteristics

	Estimate	Std. Error	z-value	Pr(>|z|)	
e:(intercept)	2.39874223	0.94294751	2.5439	0.010963	*
h:(intercept)	-0.39273883	0.81846451	-0.4798	0.631335	
p:(intercept)	3.00699086	0.93745880	3.2076	0.001338	**
e:days80miles	0.08230146	0.06738973	1.2213	0.221982	
h:days80miles	0.08573940	0.05906550	1.4516	0.146613	
p:days80miles	-0.03061558	0.06903541	-0.4435	0.657421	
e:nvehadd	0.10516199	0.15931466	0.6601	0.509196	
h:nvehadd	-0.07978520	0.13684730	-0.5830	0.559877	
p:nvehadd	0.23283709	0.16301488	1.4283	0.153200	
e:nvehannmiles	0.03475624	0.09543437	0.3642	0.715716	
h:nvehannmiles	0.08524658	0.08437088	1.0104	0.312314	
p:nvehannmiles	0.10176738	0.09762383	1.0424	0.297206	
e:googlecar	-0.12545490	0.15873784	-0.7903	0.429336	
h:googlecar	-0.03844895	0.13379784	-0.2874	0.773832	
p:googlecar	-0.21566439	0.16408750	-1.3143	0.188737	
e:childcnt	0.05497334	0.05561077	0.9885	0.322889	
h:childcnt	0.02770396	0.04746530	0.5837	0.559444	
p:childcnt	0.03495904	0.05768494	0.6060	0.544492	
e:accident	-0.09832838	0.14103178	-0.6972	0.485673	
h:accident	-0.03556739	0.12122746	-0.2934	0.769221	
p:accident	-0.03502996	0.14549075	-0.2408	0.809733	
e:preferdriving	0.19456981	0.15785809	1.2326	0.217739	
h:preferdriving	0.12897727	0.13802535	0.9344	0.350074	
p:preferdriving	0.14580141	0.16193723	0.9004	0.367930	

e:joboperateveh	0.07054496	0.23529871	0.2998	0.764322	
h:joboperateveh	0.16749324	0.20783260	0.8059	0.420298	
p:joboperateveh	0.11808620	0.24012879	0.4918	0.622888	
e:hispanic	0.09878970	0.30259004	0.3265	0.744061	
h:hispanic	0.45742748	0.25361016	1.8037	0.071284	.
p:hispanic	0.21833249	0.31126638	0.7014	0.483033	
e:ownercar	0.46229199	0.35290426	1.3100	0.190208	
h:ownercar	0.52556922	0.30119645	1.7449	0.080996	.
p:ownercar	0.18754464	0.35305121	0.5312	0.595273	
e:currgas	-0.31913080	0.48760364	-0.6545	0.512797	
h:currgas	0.20745748	0.43599648	0.4758	0.634200	
p:currgas	-0.54419414	0.49921559	-1.0901	0.275670	
e:currhyb	-0.69466287	0.61623257	-1.1273	0.259627	
h:currhyb	0.15516789	0.53888906	0.2879	0.773392	
p:currhyb	-0.48535543	0.63127680	-0.7688	0.441984	
e:currelec	-1.42163518	1.09816756	-1.2946	0.195475	
h:currelec	0.20559699	0.92074752	0.2233	0.823307	
p:currelec	-1.44482312	1.16730760	-1.2377	0.215813	
e:age	-0.00083300	0.01107795	-0.0752	0.940060	
h:age	-0.00522637	0.00939742	-0.5561	0.578109	
p:age	-0.01222071	0.01146695	-1.0657	0.286544	
e:male	0.07343449	0.15503058	0.4737	0.635730	
h:male	0.09776770	0.13296778	0.7353	0.462173	
p:male	0.01494967	0.15869359	0.0942	0.924947	
e:married	0.07123933	0.15444977	0.4612	0.644622	
h:married	0.18944629	0.13419335	1.4117	0.158026	
p:married	-0.13885764	0.15894749	-0.8736	0.382332	
e:compcollege	0.01452328	0.17218180	0.0843	0.932779	
h:compcollege	0.11503636	0.14974944	0.7682	0.442373	
p:compcollege	0.03257689	0.17664664	0.1844	0.853685	
e:hschorless	-0.12325964	0.19743799	-0.6243	0.532434	
h:hschorless	-0.10842294	0.17246701	-0.6287	0.529572	
p:hschorless	-0.05405638	0.20357468	-0.2655	0.790597	
e:ownhouse	-0.34322677	0.16629642	-2.0639	0.039023	*
h:ownhouse	-0.32252792	0.14204052	-2.2707	0.023167	*
p:ownhouse	-0.12155852	0.17175929	-0.7077	0.479115	
e:yrsdrivng	0.00405663	0.01451265	0.2795	0.779843	
h:yrsdrivng	0.00417893	0.01240811	0.3368	0.736275	
p:yrsdrivng	0.01917509	0.01499592	1.2787	0.201007	
e:fulltime	-0.14006532	0.21301809	-0.6575	0.510842	
h:fulltime	-0.17857880	0.18454739	-0.9677	0.333215	
p:fulltime	-0.16464530	0.21819369	-0.7546	0.450499	
e:parttime	0.68949529	0.33689071	2.0466	0.040693	*
h:parttime	0.40907123	0.27816204	1.4706	0.141393	
p:parttime	0.53608382	0.34642974	1.5475	0.121754	
e:hmaker	-0.12056061	0.30062040	-0.4010	0.688391	
h:hmaker	-0.23768896	0.26704532	-0.8901	0.373428	
p:hmaker	-0.21564226	0.31393457	-0.6869	0.492145	
e:student	-0.54887045	0.72838643	-0.7535	0.451124	
h:student	-1.25130373	0.70919036	-1.7644	0.077663	.
p:student	-0.81653432	0.74033212	-1.1029	0.270058	
e:white	0.21006423	0.39200304	0.5359	0.592046	
h:white	0.23697222	0.33786292	0.7014	0.483062	
p:white	0.34923676	0.40051206	0.8720	0.383222	
e:africam	0.44171263	0.45186165	0.9775	0.328302	
h:africam	0.17562167	0.39635037	0.4431	0.657696	
p:africam	0.34696758	0.45961006	0.7549	0.450299	
e:asian	0.64775686	0.55742044	1.1621	0.245210	
h:asian	0.79457291	0.48320906	1.6444	0.100100	
p:asian	0.73508801	0.57328193	1.2822	0.199757	

e:conserv	0.03757247	0.16372694	0.2295	0.818494	
h:conserv	0.07478843	0.13782102	0.5426	0.587372	
p:conserv	-0.17359205	0.16708437	-1.0389	0.298829	
e:lib	-0.08110327	0.18746427	-0.4326	0.665281	
h:lib	-0.22314132	0.16363886	-1.3636	0.172687	
p:lib	-0.14681841	0.19339538	-0.7592	0.447756	
e:west	0.10006892	0.20428852	0.4898	0.624246	
h:west	0.30174949	0.17382303	1.7360	0.082571	.
p:west	0.20933584	0.21026643	0.9956	0.319457	
e:midwest	0.42783395	0.18206023	2.3500	0.018776	*
h:midwest	0.42721911	0.15744868	2.7134	0.006660	**
p:midwest	0.21368071	0.18708735	1.1421	0.253394	
e:northeast	0.31463131	0.19512993	1.6124	0.106871	
h:northeast	0.32387710	0.16770506	1.9312	0.053455	.
p:northeast	0.24820763	0.19909095	1.2467	0.212506	
e:monthmiles	0.02106270	0.02757301	0.7639	0.444934	
h:monthmiles	-0.00557922	0.02483927	-0.2246	0.822281	
p:monthmiles	0.00115011	0.02822067	0.0408	0.967492	
e:urban	-0.10327202	0.14810193	-0.6973	0.485613	
h:urban	-0.20111709	0.12547523	-1.6028	0.108969	
p:urban	0.01542556	0.15212530	0.1014	0.919233	
e:lninc	-0.00066958	0.11750429	-0.0057	0.995453	
h:lninc	-0.13601918	0.10116719	-1.3445	0.178787	
p:lninc	0.02213326	0.12030308	0.1840	0.854030	
price	-0.06312107	0.00335389	-18.8203	< 2.2e-16	***
ocost	-0.00042469	0.02665658	-0.0159	0.987289	
lnrange	0.43864031	0.04489922	9.7694	< 2.2e-16	***
charget	-0.03094892	0.00635232	-4.8721	1.104e-06	***
network	0.44516781	0.13563082	3.2822	0.001030	**
sd.price	0.01954917	0.00953890	2.0494	0.040421	*
sd.ocost	0.14999253	0.00802655	18.6870	< 2.2e-16	***
sd.lnrange	0.46889713	0.01998517	23.4623	< 2.2e-16	***
sd.charget	0.05668105	0.01245920	4.5493	5.382e-06	***
sd.network	0.40571555	0.29461775	1.3771	0.168484	

Signif. codes: 0 ?***?0.001 ?**?0.01 ??0.05 ??0.1 ??1
Log Likelihood: -10903
BIC: 22889.74

Table B.16 and B.17 show the estimates from MIXL models with all or some parameters for alternative specific attributes following log-normal distributions. Neither of these models converged.

Table B.16
MLM with log-normally distributed taste parameters, no sociodemographic characteristics

	Estimate	Std. Error	z-value	Pr(>|z|)	
e:(intercept)	0.884638	NA	NA	NA	
h:(intercept)	-0.112450	NA	NA	NA	
p:(intercept)	0.744134	NA	NA	NA	
adprice	-2.971909	0.039064	-76.0779	< 2.2e-16	***
adocost	-7.566688	NA	NA	NA	
lnrange	-3.573625	0.564591	-6.3296	2.458e-10	***

adcharget	-5.095525	NA	NA	NA	
network	-2.212697	NA	NA	NA	
sd.adprice	0.325679	NA	NA	NA	
sd.adocost	1.407876	NA	NA	NA	
sd.lnrange	3.127768	0.401171	7.7966	6.439e-15	***
sd.adcharget	1.702522	NA	NA	NA	
sd.network	3.759481	NA	NA	NA	

Signif. codes: 0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1
Log Likelihood: -11182

Table B.17
MLM with log-normally distributed taste parameter for driving range and network, and normally distributed taste parameter for price, operating cost and charging time.

	Estimate	Std. Error	z-value	Pr(>|z|)	
e:(intercept)	0.50568620	0.14373428	3.5182	0.0004345	***
h:(intercept)	-0.08059446	0.06690040	-1.2047	0.2283217	
p:(intercept)	0.54464240	0.11656015	4.6726	2.974e-06	***
price	-0.06258830	0.00328472	-19.0544	< 2.2e-16	***
ocost	-0.00245728	0.00068256	-3.6001	0.0003181	***
lnrange	-1.86915364	0.19745954	-9.4660	< 2.2e-16	***
charget	-0.02909711	0.00609867	-4.7711	1.833e-06	***
network	-1.56512673	0.46901054	-3.3371	0.0008466	***
sd.price	0.02916245	0.00598413	4.8733	1.098e-06	***
sd.ocost	0.00339257	0.00068920	4.9225	8.546e-07	***
sd.lnrange	1.79096824	0.19923315	8.9893	< 2.2e-16	***
sd.charget	0.01251811	0.01141501	1.0966	0.2728004	
sd.network	2.24937268	NA	NA	NA	

Signif. codes: 0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1
Log Likelihood: -11133

Table B.18 show the estimates from MIXL model with fixed parameter for network, normally distributed parameters for price, operating cost, charging time and network. The stand deviation estimates were too large and sociodemographic data did not have significant impact.

Table A.18
MIXL with normally-distributed taste parameter for price, operating cost, driving range, and charging time, fixed taste parameter for network

	Estimate	Std. Error	z-value	Pr(>|z|)	
e:(intercept)	2.1502895	0.8831749	2.4347	0.0149030	*
h:(intercept)	-0.5345872	0.7801322	-0.6853	0.4931849	
p:(intercept)	3.1730036	0.8326149	3.8109	0.0001385	***
network	0.4809216	0.1306842	3.6800	0.0002332	***
e:days80miles	0.0774016	0.0640265	1.2089	0.2267016	
h:days80miles	0.0806228	0.0574195	1.4041	0.1602886	
p:days80miles	-0.0267223	0.0624163	-0.4281	0.6685567	
e:nvehadd	0.0353359	0.1513529	0.2335	0.8153987	
h:nvehadd	-0.1272399	0.1338721	-0.9505	0.3418793	

p:nvehadd	0.1361652	0.1463233	0.9306	0.3520721	
e:nvehannmiles	0.0546696	0.0924934	0.5911	0.5544765	
h:nvehannmiles	0.0706226	0.0836467	0.8443	0.3985039	
p:nvehannmiles	0.1429088	0.0898597	1.5904	0.1117547	
e:googlecar	-0.1751076	0.1506038	-1.1627	0.2449496	
h:googlecar	-0.0612510	0.1320682	-0.4638	0.6428030	
p:googlecar	-0.2644270	0.1465369	-1.8045	0.0711517	.
e:childcnt	0.0491975	0.0528029	0.9317	0.3514813	
h:childcnt	0.0280446	0.0467978	0.5993	0.5489924	
p:childcnt	0.0426084	0.0511688	0.8327	0.4050118	
e:hispanic	0.1826071	0.2740627	0.6663	0.5052213	
h:hispanic	0.4311076	0.2428740	1.7750	0.0758936	.
p:hispanic	0.3440979	0.2641901	1.3025	0.1927580	
e:ownercar	0.4417497	0.3134527	1.4093	0.1587457	
h:ownercar	0.5484589	0.2883490	1.9021	0.0571625	.
p:ownercar	0.0793686	0.3052697	0.2600	0.7948677	
e:currgas	-0.1897776	0.4570750	-0.4152	0.6779954	
h:currgas	0.2145961	0.4305233	0.4985	0.6181641	
p:currgas	-0.3559662	0.4404485	-0.8082	0.4189811	
e:currhyb	-0.5074451	0.5812995	-0.8729	0.3826906	
h:currhyb	0.1637694	0.5340194	0.3067	0.7590922	
p:currhyb	-0.2690894	0.5602985	-0.4803	0.6310420	
e:currelec	-1.4350596	1.1126826	-1.2897	0.1971446	
h:currelec	0.2057127	0.9261583	0.2221	0.8242252	
p:currelec	-0.9939472	1.0630944	-0.9350	0.3498106	
e:age	0.0021805	0.0106001	0.2057	0.8370195	
h:age	-0.0044884	0.0092078	-0.4875	0.6259392	
p:age	-0.0099620	0.0102605	-0.9709	0.3315971	
e:male	0.0589506	0.1418782	0.4155	0.6777751	
h:male	0.1010986	0.1257593	0.8039	0.4214519	
p:male	0.0171956	0.1378748	0.1247	0.9007458	
e:married	0.0804429	0.1520233	0.5291	0.5967023	
h:married	0.1583205	0.1330757	1.1897	0.2341633	
p:married	-0.0985415	0.1472252	-0.6693	0.5032884	
e:compcollege	0.0259974	0.1691948	0.1537	0.8778829	
h:compcollege	0.1057923	0.1491347	0.7094	0.4780924	
p:compcollege	0.0573437	0.1643549	0.3489	0.7271630	
e:hschorless	-0.0448438	0.1915013	-0.2342	0.8148532	
h:hschorless	-0.0772314	0.1707458	-0.4523	0.6510398	
p:hschorless	0.0346845	0.1856326	0.1868	0.8517824	
e:ownhouse	-0.2878406	0.1552776	-1.8537	0.0637799	.
h:ownhouse	-0.2751809	0.1382466	-1.9905	0.0465350	*
p:ownhouse	-0.0835201	0.1509225	-0.5534	0.5799913	
e:yrsdrivng	-0.0027086	0.0137873	-0.1965	0.8442511	
h:yrsdrivng	0.0019224	0.0119918	0.1603	0.8726395	
p:yrsdrivng	0.0132400	0.0133605	0.9910	0.3216919	
e:fulltime	-0.1205559	0.2099395	-0.5742	0.5658047	
h:fulltime	-0.1720250	0.1855160	-0.9273	0.3537821	
p:fulltime	-0.1311731	0.2016349	-0.6505	0.5153385	
e:parttime	0.5681317	0.2935583	1.9353	0.0529500	.
h:parttime	0.3648550	0.2633233	1.3856	0.1658757	
p:parttime	0.3722498	0.2849273	1.3065	0.1913918	
e:hmaker	-0.0272062	0.2996354	-0.0908	0.9276535	
h:hmaker	-0.1449715	0.2698936	-0.5371	0.5911689	
p:hmaker	-0.1150675	0.2907123	-0.3958	0.6922437	
e:student	-0.6165588	0.6636682	-0.9290	0.3528805	
h:student	-1.2915836	0.6957215	-1.8565	0.0633871	.
p:student	-0.8457512	0.6482982	-1.3046	0.1920389	
e:white	0.1804052	0.3737396	0.4827	0.6293067	
h:white	0.2007313	0.3363565	0.5968	0.5506533	

p:white	0.3460230	0.3588147	0.9643	0.3348705	
e:africam	0.3771287	0.4339194	0.8691	0.3847807	
h:africam	0.1213359	0.3941233	0.3079	0.7581868	
p:africam	0.3377249	0.4171719	0.8096	0.4181942	
e:asian	0.4996295	0.5269821	0.9481	0.3430807	
h:asian	0.6887151	0.4756300	1.4480	0.1476154	
p:asian	0.5782109	0.5125474	1.1281	0.2592726	
e:conserv	0.0406159	0.1519994	0.2672	0.7893069	
h:conserv	0.0748087	0.1334826	0.5604	0.5751805	
p:conserv	-0.1634453	0.1471303	-1.1109	0.2666167	
e:lib	-0.0374675	0.1748406	-0.2143	0.8303168	
h:lib	-0.2197086	0.1594644	-1.3778	0.1682679	
p:lib	-0.0918149	0.1697421	-0.5409	0.5885711	
e:west	0.1442591	0.1879607	0.7675	0.4427868	
h:west	0.3385549	0.1683153	2.0114	0.0442797	*
p:west	0.2271478	0.1832327	1.2397	0.2150980	
e:midwest	0.3970385	0.1720639	2.3075	0.0210266	*
h:midwest	0.4104784	0.1528483	2.6855	0.0072415	**
p:midwest	0.1789451	0.1672075	1.0702	0.2845303	
e:northeast	0.2176491	0.1875385	1.1606	0.2458222	
h:northeast	0.2922942	0.1647621	1.7740	0.0760569	.
p:northeast	0.1135586	0.1813796	0.6261	0.5312608	
e:monthmiles	0.0145535	0.0269215	0.5406	0.5887894	
h:monthmiles	-0.0020977	0.0246717	-0.0850	0.9322424	
p:monthmiles	-0.0110143	0.0261683	-0.4209	0.6738260	
e:urban	-0.0359149	0.1389417	-0.2585	0.7960298	
h:urban	-0.1797444	0.1225507	-1.4667	0.1424594	
p:urban	0.0846667	0.1348067	0.6281	0.5299645	
e:lninc	0.0154544	0.1122758	0.1376	0.8905196	
h:lninc	-0.1267077	0.0988995	-1.2812	0.2001315	
p:lninc	0.0184173	0.1076010	0.1712	0.8640954	
price	-0.0564325	0.0032612	-17.3043	< 2.2e-16	***
ocost	-0.0468616	0.0259416	-1.8064	0.0708518	.
lnrange	-0.6686374	0.0767265	-8.7146	< 2.2e-16	***
charget	-0.0278842	0.0062472	-4.4635	8.064e-06	***
sd.price	0.0248731	0.0083841	2.9667	0.0030101	**
sd.ocost	0.1438331	0.0076079	18.9058	< 2.2e-16	***
sd.lnrange	0.6208095	0.0389512	15.9381	< 2.2e-16	***
sd.charget	0.0556292	0.0132905	4.1856	2.844e-05	***

Signif. codes: 0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1
Log Likelihood: -11001

Table B.19 and B.20 show the estimates for LC models with three and four classes (clusters).

None of them converged.

Table B.19

LC model with 3 classes, with same sociodemographic characteristics as model A

	Estimate	Std. Error	z-value	Pr(>|z|)	
class.1.price	0.01638800	0.02618110	0.6259	0.5313492	
class.1.ocost	-0.07110363	0.01929936	-3.6842	0.0002294	***
class.1.lnrange	1.10589554	0.24298652	4.5513	5.332e-06	***
class.1.charget	0.03118432	0.05369490	0.5808	0.5613963	

class.1.network	0.39412428	NA	NA	NA	
class.2.price	-0.04447094	0.00424233	-10.4827	< 2.2e-16	***
class.2.ocost	-0.00327098	0.00074561	-4.3870	1.149e-05	***
class.2.lnrange	0.36465032	0.02328765	15.6585	< 2.2e-16	***
class.2.charget	-0.03204794	0.00786526	-4.0746	4.609e-05	***
class.2.network	0.95886073	0.19734652	4.8588	1.181e-06	***
class.3.price	-0.08390944	0.00679314	-12.3521	< 2.2e-16	***
class.3.ocost	-0.00097735	0.00058602	-1.6678	0.0953599	.
class.3.lnrange	0.10989373	0.03243908	3.3877	0.0007048	***
class.3.charget	-0.03023919	0.01458603	-2.0732	0.0381573	*
class.3.network	0.68250409	0.22353195	3.0533	0.0022636	**
(class)2	1.36850849	0.03858625	35.4662	< 2.2e-16	***
(class)3	0.70358609	0.06019501	11.6884	< 2.2e-16	***

Signif. codes: 0 '***'0.001 '**'0.01 '*'0.05 '.'0.1 ''1
Log Likelihood: -11098

Table B.20
LC model with 4 classes, with same sociodemographic characteristics as model A

	Estimate	Std. Error	z-value	Pr(>|z|)	
class.1.price	-0.02965620	0.00650362	-4.5600	5.116e-06	***
class.1.ocost	-0.00064180	0.00119084	-0.5389	0.5899214	
class.1.lnrange	0.08494112	0.05267186	1.6126	0.1068212	
class.1.charget	-0.04570033	0.01189938	-3.8406	0.0001228	***
class.1.network	5.01445278	1.16050817	4.3209	1.554e-05	***
class.2.price	-0.08774254	0.00692526	-12.6699	< 2.2e-16	***
class.2.ocost	-0.00123296	0.00059299	-2.0792	0.0375972	*
class.2.lnrange	0.17073255	0.02870950	5.9469	2.733e-09	***
class.2.charget	-0.02865875	0.01391916	-2.0589	0.0394997	*
class.2.network	0.10392320	0.23507708	0.4421	0.6584303	
class.3.price	0.01445979	0.05751992	0.2514	0.8015145	
class.3.ocost	-0.08433991	0.04828181	-1.7468	0.0806676	.
class.3.lnrange	1.82109296	0.65310139	2.7884	0.0052973	**
class.3.charget	0.09709301	0.23506591	0.4130	0.6795730	
class.3.network	0.36170912	NA	NA	NA	
class.4.price	-0.06807404	0.00884260	-7.6984	1.377e-14	***
class.4.ocost	-0.00734492	0.00162751	-4.5130	6.392e-06	***
class.4.lnrange	0.68106756	0.05736111	11.8733	< 2.2e-16	***
class.4.charget	-0.01417555	0.01342878	-1.0556	0.2911466	
class.4.network	-2.17331911	0.41651838	-5.2178	1.810e-07	***
(class)2	-0.00164955	0.08594951	-0.0192	0.9846878	
(class)3	-1.23899832	0.08298647	-14.9301	< 2.2e-16	***
(class)4	0.04872844	0.09211275	0.5290	0.5967995	

Signif. codes: 0 '***'0.001 '**'0.01 '*'0.05 '.'0.1 ''1
Log Likelihood: -10985

Table B.21 and B.22 show the estimates for MML models with normally distributed parameters for alternative specific attributes in each class (cluster). None of them converged.

Table B.21
MML model with 2 classes

	Estimate	Std. Error	z-value	Pr(>|z|)	
class.1.price	-0.06078462	0.00328771	-18.4884	< 2.2e-16	***
class.1.ocost	-0.00211343	0.00048799	-4.3309	1.485e-05	***
class.1.lnrange	0.24360042	NA	NA	NA	
class.1.charget	-0.03498637	0.00647195	-5.4058	6.450e-08	***
class.1.network	1.41050391	NA	NA	NA	
class.2.price	-0.04963821	0.01433656	-3.4624	0.0005355	***
class.2.ocost	-0.05349411	NA	NA	NA	
class.2.lnrange	1.12409988	0.09550444	11.7701	< 2.2e-16	***
class.2.charget	-0.02025956	0.03093676	-0.6549	0.5125515	
class.2.network	-4.95164377	0.63493996	-7.7986	6.217e-15	***
class.1.sd.price	0.04132114	0.00421140	9.8117	< 2.2e-16	***
class.1.sd.ocost	0.00379512	0.00057034	6.6541	2.850e-11	***
class.1.sd.lnrange	0.14649114	NA	NA	NA	
class.1.sd.charget	0.01619794	0.01026817	1.5775	0.1146827	
class.1.sd.network	0.99528198	NA	NA	NA	
class.2.sd.price	0.04564707	0.02450288	1.8629	0.0624726	.
class.2.sd.ocost	0.03040704	NA	NA	NA	
class.2.sd.lnrange	0.25619929	NA	NA	NA	
class.2.sd.charget	0.04581873	0.04382568	1.0455	0.2958027	
class.2.sd.network	1.01492200	0.69047744	1.4699	0.1415931	
(class)2	-1.91318577	0.04194316	-45.6138	< 2.2e-16	***
GenerationX:class2	0.32482361	0.10007454	3.2458	0.0011711	**
class2:BabyBoom	0.19899661	0.09664932	2.0590	0.0394985	*
class2:Silent	0.29598418	0.16352467	1.8100	0.0702915	.

Signif. codes: 0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1

Log Likelihood: -11060

Table B.22

MML model with 2 classes

	Estimate	Std. Error	z-value	Pr(>|z|)	
class.1.price	-0.06076551	0.00335151	-18.1308	< 2.2e-16	***
class.1.ocost	-0.00166767	0.00046113	-3.6165	0.0002986	***
class.1.lnrange	0.23061716	NA	NA	NA	
class.1.charget	-0.03525529	0.00676392	-5.2123	1.866e-07	***
class.1.network	1.75356793	NA	NA	NA	
class.2.price	-0.05261330	0.01415757	-3.7163	0.0002022	***
class.2.ocost	-0.01403389	0.00444472	-3.1574	0.0015917	**
class.2.lnrange	1.36813861	NA	NA	NA	
class.2.charget	-0.00900348	0.02458494	-0.3662	0.7142015	
class.2.network	-4.62415238	NA	NA	NA	
class.1.sd.price	0.03900064	0.00435963	8.9459	< 2.2e-16	***
class.1.sd.ocost	0.00352573	0.00049589	7.1099	1.162e-12	***
class.1.sd.lnrange	0.12344927	NA	NA	NA	
class.1.sd.charget	0.02004381	0.01074667	1.8651	0.0621649	.
class.1.sd.network	1.25574256	NA	NA	NA	
class.2.sd.price	0.05148254	0.01775814	2.8991	0.0037424	**
class.2.sd.ocost	0.01276143	0.00353948	3.6054	0.0003116	***
class.2.sd.lnrange	0.71691488	NA	NA	NA	
class.2.sd.charget	0.02778357	0.03882638	0.7156	0.4742477	
class.2.sd.network	0.11640492	0.53719105	0.2167	0.8284485	
(class)2	-2.87553558	0.24544738	-11.7155	< 2.2e-16	***
GenerationX:class2	0.48500418	0.09817608	4.9401	7.806e-07	***
class2:BabyBoom	0.23685542	0.09996999	2.3693	0.0178235	*
class2:Silent	0.47768988	0.16081698	2.9704	0.0029742	**
class2:days80miles	0.21501843	0.02816657	7.6338	2.287e-14	***
class2:currgas	0.65322334	0.16871200	3.8718	0.0001080	***

```
class2:married      0.30718961  0.07372302   4.1668 3.089e-05 ***
class2:parttime     0.80541711  0.09741108   8.2682 2.220e-16 ***
class2:student     -6.40532680          NA       NA        NA
class2:africam      0.36126653  0.12265222   2.9455 0.0032248 **
class2:asian        0.31358719  0.19794026   1.5843 0.1131365
class2:lib         -0.44607943  0.08718125  -5.1167 3.109e-07 ***
class2:west         0.08792534  0.09374274   0.9379 0.3482738
class2:midwest      0.54762674  0.07696187   7.1156 1.115e-12 ***
class2:lninc       -0.07806329  0.05063861  -1.5416 0.1231765
---
Signif. codes:  0 ‘***’0.001 ‘**’0.01 ‘*’0.05 ‘.’0.1 ‘’1
Log Likelihood: -11040
```

Appendix C: Supporting charts for case study

Fig. C.53 – Fig. C.55 shows the marginal manufacturing cost regrading driving range by battery cost for 2016 Ford Focus EV, 2015 Tesla S 60 and 2016 Tesla S 90D.

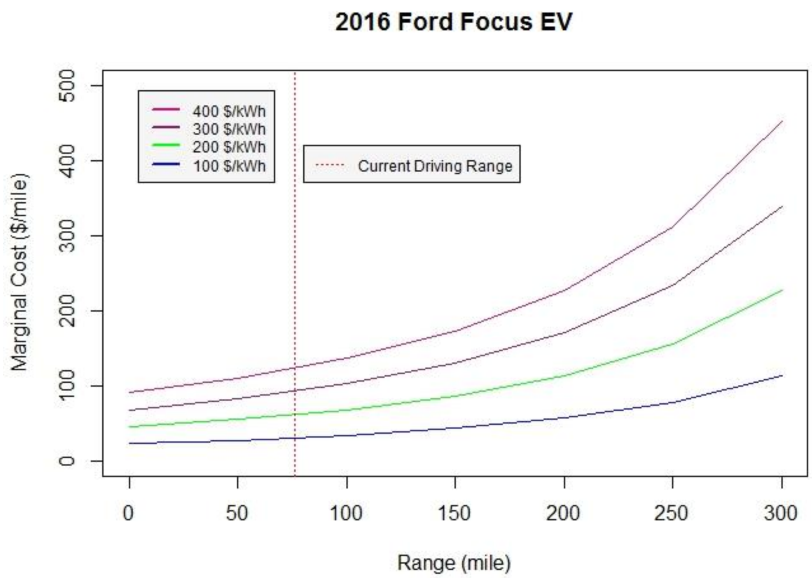


Fig. C.53 Marginal cost regarding driving range, 2016 Ford Focus EV

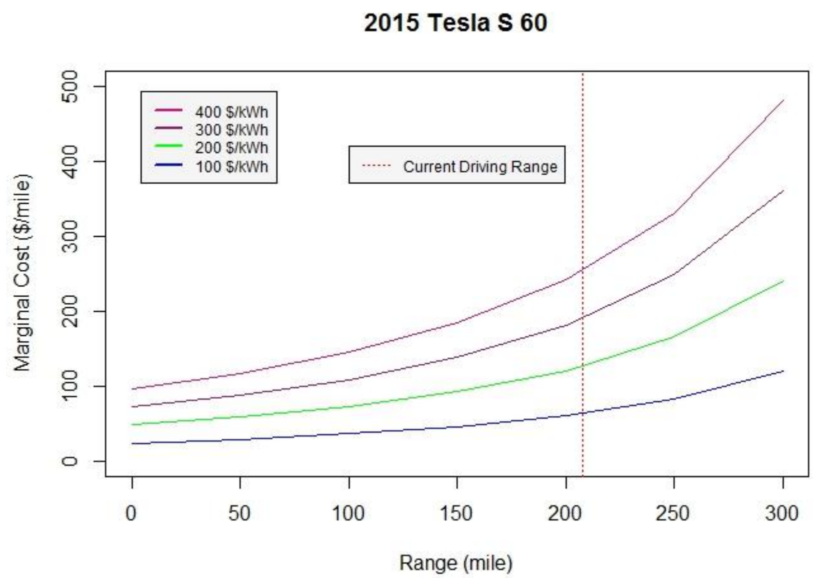


Fig. C.54 Marginal cost regarding driving range, 2015 Tesla S 60

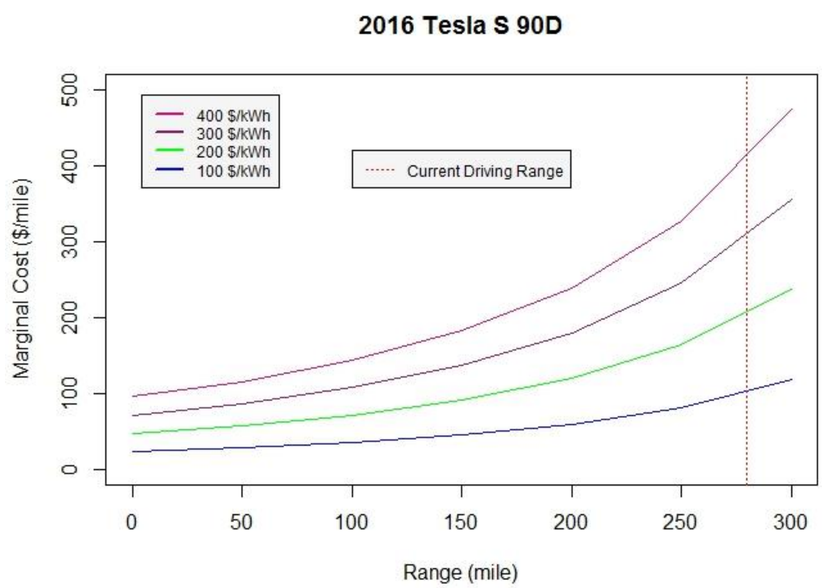


Fig. C.55 Marginal cost regarding driving range, 2016 Tesla S 90D

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