Project Report

An Exploratory Analysis to Estimate the Value of Free Charging Bundle in Electric Vehicle Purchases

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract

Our research establishes a national estimate of the willingness-to-pay (WTP) for a free charging bundle in the United States electric vehicle market. Using a stated choice experiment conducted using a probability-based sample from an internet panel, 36 choice scenarios were generated with 9 scenarios received per respondent. Individuals chose between three vehicles (two EVs and a comparable gasoline vehicle) with varying vehicle attributes: purchase price, driving range, annual fuel cost, and years of free charging. For EVs, the free charging bundle was offered at four levels: zero, one, two, and three years. Results from the mixed logit and latent class analysis showed heterogeneity in the sensitivity to the free charging time scale with a significant share of the population showing no sensitivity to a single year of free charging. All population segments experienced some WTP for free charging at the two- and three-year time frames.

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SUMMARY

The bundling of a free item or service in a purchase can result in additional perceived valuation over the consumer's valuation of the item in isolation. This additional valuation can cause a product bundle to become significantly more desirable when the bundled item is offered for free versus a marginally higher price. As policymakers and businesses consider expanding electric vehicle infrastructure and creating pricing structures to increase EV demand, there is limited guidance on the value that consumers place on free charging. Langbroek and colleagues found a significant willingness-to-pay for EVs under a free public charging policy. They also found that free public charging had a greater effect on individuals who were actively interested in purchasing a new EV.

Our research establishes a national estimate of the willingness-to-pay (WTP) for a free charging bundle in the United States electric vehicle market. Using a stated choice experiment conducted using a probability-based sample from an internet panel, 36 choice scenarios were generated with 9 scenarios received per respondent. Individuals chose between three vehicles (two EVs and a comparable gasoline vehicle) with varying vehicle attributes: purchase price, driving range, annual fuel cost, and years of free charging. For EVs, the free charging bundle was offered at four levels: zero, one, two, and three years. Results from the mixed logit and latent class analysis showed heterogeneity in the sensitivity to the free charging time scale with a significant share of the population showing no sensitivity to a single year of free charging. All population segments experienced some WTP for free charging at the two- and three-year time frames. Additionally, an error component latent class model was estimated to account for heterogeneity in preferences and attribute non-attendance. About 35% of respondents had no interest in electric vehicles, while over 60% of respondent was responsive to at least a three-year duration of a free charging bundle. Normalizing willingness-to-pay for free charging by year, respondents who were attentive to 2 or 3 years of free charging showed similar willingness-to-pay to the average cost of gasoline fueling (in 2018). Respondents attentive to all durations of free charging showed valuations that were about twice as much as the cost of fueling an average gasoline vehicle.

The research findings can help in assessing prospective policies regarding incentive programs involving free charging, the installation and pricing structures of public charging infrastructure, and developing market campaigns for PEVs.

INTRODUCTION

Internationally, local, regional, and national governments are currently analyzing, proposing, and executing policies to encourage electric vehicle (EV) adoption (USDOE, 2020). As policymakers and businesses consider expanding electric vehicle infrastructure and creating pricing structures to increase EV demand, there is limited guidance on the value that consumers place on charging and specifically free charging.

The average cost of charging an EV in the US is about $0.15/kWh corresponding to $3000 - $10,500 in predicted fuel cost savings over a 15-year time horizon (Borlaug et al., 2020). McMahon (2018) states that the average annual operating cost of an EV in the US ($485) is comparatively less to that of a conventional gasoline vehicle ($1,200). Implementation of widespread charging discount programs has not been performed. Some companies have offered such programs, such as Tesla's rollout of their supercharger network. Initially offering free charging throughout the vehicle's lifetime, in 2018-2019, Tesla reduced the offer to two years of free charging bundle with the purchase of a new Model 3 (Scooter Doll, 2021).

The EV Project found that 15% of participants primarily used public chargers because they could find free charging. And 26% of participants believed that making public charging free would increase their likelihood of using public chargers. Langbroek and colleagues (2016) used a stated choice experiment to study EV purchasing preference in the presence of a hypothetical free public charging. They found a significant willingness-to-pay for a free public charging system of 14,500 SEK (≈1575 USD). They also found that free public charging had a greater effect on individuals who were actively interested in purchasing a new EV. Maness and Lin (2019) briefly reviewed the literature on the value of free and found that bundling free items increased the attractiveness of products beyond the actual value of the bundled object. They suggest that providing free charging could increase EV adoption. To the authors' knowledge, no publicly available sources provide a valuation of a free charging bundle by years of free charging. David et al. (2019) state that amongst all the traditional restrictions of EVs, the scarcity of charging infrastructure is the most significant hurdle that has the potential to reverse the growth of a developing EV market.

This study establishes a national estimate of the willingness-to-pay (WTP) for a free charging bundle in the United States electric vehicle market. The willingness-to-pay provides an estimate of the additional value placed on the free charging bundle versus charging cost discount.

LITERATURE REVIEW

Past researchers who studied preferences for a vehicle choice incorporated stated preference methods into their work. One such research by Hidrue et al. (2011) concentrated on finding the demand for EVs and its feasibility to the general market of current and future car owners. A latent class random utility model was estimated to analyze the data collected with the help of 3,029 respondents. Consequently, the estimated parameters from the model were used to find out the willingness-to-pay for EVs based on five primary attributes: driving range, charging time, fuel-cost saving, pollution reduction and performance. In the stated preference survey, the respondents were asked to choose between their preferred gasoline vehicle and two electric versions of their preferred gasoline vehicle with distinctive attributes. The final stated preference survey used was then modified several times with the help of focus groups, pretest surveys, and miscellaneous reviews. Finally, the survey was divided into four categories: 1. Car ownership and driving habits, 2. Stated preference questions on conventional EVs, 3. Stated preference questions on vehicle-to-grid EVs, 4. Attitudinal and demographical questions. Both categories consisted of what the researcher's termed as 'cheap talk' which basically is the description of the hypothetical scenario that the stated preference questions are based upon. In SP section of the survey, the respondents were presented with multiple hypothetical scenarios. These hypothetical scenarios were designed to overcome the challenges and the limitations that the respondent faced in the real world so that the response obtained was more inclined towards actuality rather than being influenced by conjectures and assumptions.

Liao et al. (2017) discussed a finding by Sierzchula et al. (2014), affirming that numerous policies have been launched and executed by the government to incite EV production and adoption. To examine the consumers' preference of EVs, numerous experimental studies have been done over the last decade, with 2009 and 2010 signifying the years of the EV market's actual growth. There have been comparatively fewer studies entirely based on BEVs. Hidrue et al. (2011) performed one such analysis of US consumers' preference of EVs in 2009 by deploying a latent-class model. Molin et al. (2012) conducted a test using a mixed logit model in 2011 on the Netherland consumer's EV preference. The results suggested that attributes such as purchase price, driving range, and fast charging availability impacted consumers' EV purchase preferences significantly. A subset of the work also discussed that a subsidy of 5000 euro and fast-charging facilities at charging stations both could encourage EV purchase. However, providing fast charging would be cheaper than subsidizing the purchase price. Thus, fast charging was considered to be a more cost-effective option.

Another similar study was done by Rasouli and Timmermans (2013) in the Netherlands using a mixed logit model where two distinct mixed logit models were estimated. One of the mixed logit models had random parameters for vehicle and contextual attributes and incorporated fixed effects of social network attributes. The second one included random effect for the social networks and fixed effects for the vehicle and contextual attributes. The results from the study reflected that vehicle attributes are the most significant in decision making concerning EVs, supported by the impacts of the social connections (social network attributes); however, the effect of the social influence is considerably lesser in comparison.

Some studies utilized the hybrid voice model to estimate consumers' EV preferences (Jensen et al., 2013; Glerum et al., 2014; Kim, Rasouli, and Timmermans, 2014). The result from Jensen et al. (2013) indicated that consumer's EV preference changed majorly after an active physical experience with EVs. The driving range, top speed, cost of charging, battery life, and charging locations were significant attributes. The environmental effect of the EVs positively influenced the consumers. The results by Glerum et al. (2014) mentioned two major factors inducing utility and disutility in an individual's vehicle choice. A higher incentive of about 5000 CHF(CHF is used to denote Swiss Franc) encouraged EV purchase whereas, high operating costs (5.40 CHF per 100 kilometers) repressed it. The individuals were also willing to pay an additional price of 1110 CHF on the EV's purchase price, considering if the monthly battery leasing cost was reduced by 10 CHF.

Other related research involved BEVs, HEVs, and PHEVs. Some analysis was done by using basic multinomial logit models (Mau et al., 2008; Musty and Kockelman, 2011; Achtnicht et al., 2012), while others performed analysis through mixed logit models (Mabit and Fosgerau, 2011; Maness and Cirillo, 2012; Hackbarth and Madlener, 2013; Hoen and Koetse, 2014; Tanaka et al., 2014 and Helveston et al., 2015). The cited studies involved a few attributes with proven significance in a global setup; the EV's purchase price, operation cost, and the driving range.

Tanaka et al. (2014) estimated the willingness-to-pay (WTP) for BEVs and PHEVs in the US and Japan. The results for the United States indicated that the consumers were majorly influenced by the fuel cost (charging cost for EVs) and the availability of the fueling station (charging stations in case of EVs). The fuel cost reduction was also compared across the states of California, Texas, Michigan, and New York. It was found to be more significant in California as compared to the other states. Another significant factor was the subsidies in the purchase price of the EVs.

In another study, the driving range and refueling were the significant attributes affecting consumer's vehicle preferences. Other major attributes that influenced the vehicle choice were the weight of the car, annual mileage (MPG or MPGe), and the vehicle's commuting frequency. It was also discovered that individuals with low annual mileage were early adopters of the EVs (Hoen and Koetse, 2014). Hackbarth and Madlener, 2013 suggested that vehicle consumers are willing to pay substantial amounts for vehicles with enhanced features, where the amount varies with vehicle type. The study also indicated that EV adoption required the introduction and implementation of different policies.

Other work on a similar topic highlighted on how to use stated preference in the electric vehicle research. Authors suggested that to advance the application of SP approach in EV research, several prime factors should be considered. Those factors would help in understanding an individuals' behavioral response to vehicle choice in a potentially more comprehensible manner. Choices can be represented as a function of these factors, namely: vehicle features, socio-economic characteristics, attitudinal factors, travel pattern and incentives and policies (Elnaz et al., 2015).

Although challenging, stated preference approach has a lot of potential over limitations. These limitations can be significantly overcome by referring to past research. One such research has listed several probable misjudgments, missing concepts, underestimated factors, inefficient data processing and ambiguity that can be overcome in miscellaneous ways (Massiani, 2014).

SURVEY DESIGN AND METHODOLOGY

The current study used stated preference data collected between the 10th of July and the 25th of August 2020. The survey collected information about respondents, respondent's household characteristics, their commutes, vehicles, socio-demographic factors, and multiple stated preference questions with regards to EV charging. The survey design was conceptually divided into five parts.

1. Household characteristics were collected, including number of people, their age, number of workers, household annual income, residence type, number of drivers.
2. Commute characteristics were collected, including primarily used vehicle, employment status, employment type, time taken to travel between work and home, number of miles

driven previous year, usual mode of transportation to work/school, work from home, parking place at school/work, driven an EV, familiarity with an EV, total number of long-distance trips over last three months.
3. Vehicle characteristics were collected, including Make and Model, Annual Mileage, Year, Hybrid status.
4. Socio-economic details were collected, including Gender, Age, Education Level, Martial Status.
5. Stated preference scenario questions on charger choice and the vehicle choice

Stated Preference Introduction

The data for this study was collected using a web-based stated preference survey. Hensher (1994) stated that SP (stated preference) methods are famously used in travel behavior because of its ability to unravel the behavioral reactions to varying choice situations which the market is not accustomed with. SP methods are also known for their ability to imitate reality in a way that even revealed preference study fails to predict the behavioral reactions. There has only been very limited research done that recorded the modeling of the charging choices of BEV drivers using stated preference survey (Wen, et al., 2016). In this study, it is suggested that SP approach is advantageous for behavioral studies because of its ability to accommodate systematically varying scenarios which otherwise can be proved correlated in revealed preference. They also reflect upon the cons of a SP approach having hypothetical bias generated due to unfamiliar choice situations. Wen et al. (2016) recommends that this bias can be alleviated by providing respondents with choice situations that they face on a more regular basis.

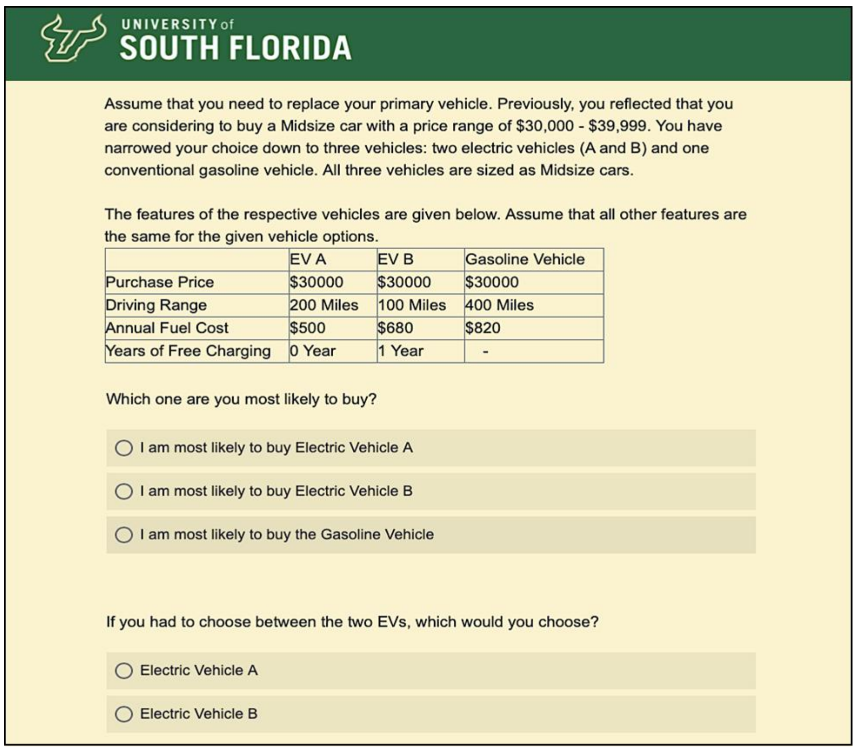
In stated preference section of the survey the respondents were presented with hypothetical scenarios. These hypothetical scenarios were designed to overcome the challenges and the limitations that we face in the real world such as, in this case, availability of chargers and number of people owning a BEV. The SP section of the survey started with an introduction which included basic definitions of an EV (electric vehicle) stating 'Electric vehicles are run by electricity stored in the vehicle's batteries. These batteries are charged using an electric charger and no liquid fuel (such as gasoline) is needed to fuel this vehicle. An electric vehicle is not the same as a hybrid vehicle.' This definition existed to answer the basic curiosity of the people who were less familiar with that technology. It was followed by the short explanation of terms which were used to define fundamental characteristics of an EV. These terms can be explained as

1. *Fuel*: Runs on electricity stored in the vehicle's batteries. This electricity typically comes from the power grid, such as an outdoor socket attached to an electric battery charger.
2. *Fueling*: The vehicle's batteries are charged by plugging into a charging plug for 15 to 60 minutes.
3. *Range*: Electric vehicles can operate until their batteries are depleted. Then the batteries must be recharged at a charging station or home. In the next section, the scenario description for the charger choice is discussed.

Scenario Setup and Description

The respondents were asked to imagine that they had to buy a vehicle to replace their current one. They had to choose between three vehicles, two were electric vehicles and one was a conventional gasoline vehicle. These vehicles had varying characteristics including purchase price, driving range, annual fuel cost and years of free charging. Assuming that each vehicle was identical in all other aspects not shown in the vehicle descriptions, they were given nine different scenarios and asked to choose between three vehicles.

A design for the vehicle choice is presented in Figure 1. The follow-up question consists of two choices, Electric Vehicle A or Electric Vehicle B. This question is added as a back-up to when and if a respondent selects a gasoline vehicle in the primary stated preference question, we can still have a behavioral response to when only EVs are provided as choices. This question identifies the behavior of respondents where their responses are observed for varying vehicle choices, one inclusive of Gasoline vehicle and EVs and the other only having EVs as options to choose from.


UNIVERSITY of SOUTH FLORIDA

Assume that you need to replace your primary vehicle. Previously, you reflected that you are considering to buy a Midsize car with a price range of $30,000 - $39,999. You have narrowed your choice down to three vehicles: two electric vehicles (A and B) and one conventional gasoline vehicle. All three vehicles are sized as Midsize cars.

The features of the respective vehicles are given below. Assume that all other features are the same for the given vehicle options.

	EV A	EV B	Gasoline Vehicle
Purchase Price	$30000	$30000	$30000
Driving Range	200 Miles	100 Miles	400 Miles
Annual Fuel Cost	$500	$680	$820
Years of Free Charging	0 Year	1 Year	-

Which one are you most likely to buy?

- I am most likely to buy Electric Vehicle A
- I am most likely to buy Electric Vehicle B
- I am most likely to buy the Gasoline Vehicle

If you had to choose between the two EVs, which would you choose?

- Electric Vehicle A
- Electric Vehicle B

Figure 1 An example of the vehicle choice experiment as presented to the respondents

The choice experiment had an additional block before the primary SP question block that included questions where the individual choices were linked to the value that appeared on the SP questions. To allow for an adaptive design, respondents were first asked "*Assuming that you were to buy a car shortly, which one are you are most likely to prefer?*" The respondents then selected from

- Distinct car sizes: small, midsize, and large cars; SUV; Minivan; and pickup truck
- Target purchase price: six ranges of values
- Number of miles that the vehicle will be driven per year under non-COVID-19 conditions.

The target purchase price provided a reference price for the purchase price attribute. The vehicle size was used to develop a low, median, and high fuel economy based on current conventional and electric vehicles in that size category. For example, when a respondent was asked about the type of a vehicle, assuming they would need to buy a car soon, the question offered following options: compact car, midsize car, large car, SUV, pick-up truck, or a van. That vehicle type that respondents pick as their preference is then used to determine the value of fuel efficiency in the stated preference scenario questions. Suppose a respondent picks a large car, then the possible values of efficiencies would be 29, 38, 54 mpg for gasoline vehicle and 75, 95, 115 mpge for EVs. The mileage was then used to adapt the fuel cost based on the fuel economy levels. The value of fuel efficiency thus obtained was deployed in the back end for the calculation of annual fuel cost. Equation (1) and (2) summarize the value of the annual fuel cost used for the vehicles with the respective characteristics.

$$\underset{\textit{(Gasoline Vehicle)}}{\text{Annual Fuel Price}} = \underset{\textit{(miles)}}{\text{Distance covered in 1 year}} \times \underset{\textit{(\$2.5/US gallon)}}{\text{Fuel Price}} \times \underset{\textit{(1 gallon / mpg)}}{\text{Fuel Consumption}} \tag{1}$$

$$\underset{\textit{(Electric Vehicle)}}{\text{Annual Fuel Price}} = \underset{\textit{(miles)}}{\text{Distance covered in 1 year}} \times \underset{\textit{(\$0.13KWhr)}}{\text{Electricity Price}} \times \underset{\textit{(33.7KWhr / mpge)}}{\text{Fuel Consumption}} \tag{2}$$

The experimental design for the stated preference experiments was generated using a software called NGENE. The four attributes used are, *purchase price*, *driving range*, *annual fuel cost* and *years of free charging* (Table 1).

Table 1 Attribute levels for vehicle choice experiment

Attribute	Levels	
Purchase price (relative to your future vehicle choice)	Same, 10% higher, 20% higher	
Driving range	100 miles, 200 miles, 300 miles	
Annual fuel cost	EV	Gasoline
(The levels:1,2,3 was adapted to the previous selection of the respondent)	1, 2, 3	1, 2, 3
Years of free charging	0 year, 1 year, 2 years, 3 years	

The Table 2 and Table 3 display the levels that were adapted according to the previous selection of the respondent.

Table 2 Levels of the attributes for gasoline vehicles

Attribute	Levels					
Purchase Price of the current vehicle	Less than \$15,000 \$15,000 - \$19,999 \$20,000 - \$29,999 \$30,000 - \$39,999 \$40,000 - \$49,999 \$50,000 - \$59,999 \$60,000 and above					
Driving Range	400 miles					
Fuel Efficiency (Combined MPG)	Compact cars	Midsize cars	Large cars	SUV	Pickup Trucks	Vans
1 2 3	25 33 40	29 38 56	29 38 54	15 20 25	11 17 25	14 18 20

Table 3 Levels of the attributes for electric vehicles

Attributes	Levels					
Purchase Price relative to your current vehicle choice	Same 10% higher 20% higher					
Driving Range (fully charged battery)	100 miles 200 miles 300 miles					
Fuel Efficiency (Combined MPGe)	Compact cars	Midsize cars	Large cars	SUV	Pickup Trucks	Vans
1 2 3	100 115 130	80 110 140	75 95 115	75 99 115	15 25 30	75 90 110
Years of free charging	0 years 1 year 2 years 3 years					

The experimental design for the stated preference experiments (Table 4) was generated using an orthogonal design approach in a software called NGENE. Orthogonality defines the property where the attribute correlations are non-existing within the alternatives but not necessarily between the alternatives. In other words, all the attributes should be such that they can be estimated individually, and the levels of the attributes were uncorrelated for each attribute column generated.

Table 4 Vehicle choice experimental design

		Electric Vehicle A				Electric vehicle B				Gasoline Vehicle		
Scenarios	Block	Purchase Price	Driving Range	Annual Fuel Cost	Years of Free Charging	Purchase Price	Driving Range	Annual Fuel Cost	Years of Free Charging	Purchase Price	Driving Range	Annual Fuel Cost
1	1	price20	range200	EVFC1	year0	price20	range300	EVFC1	year0	price10	400	GASFC2
2	1	price20	range300	EVFC2	year1	price10	range200	EVFC2	year3	price20	400	GASFC1
3	1	price10	range200	EVFC1	year1	price20	range300	EVFC2	year0	price20	400	GASFC1
4	1	price10	range300	EVFC2	year0	price10	range200	EVFC1	year1	price10	400	GASFC2
5	1	price20	range100	EVFC2	year3	price20	range300	EVFC1	year1	price10	400	GASFC0
6	1	price20	range100	EVFC2	year3	price0	range300	EVFC1	year1	price0	400	GASFC0
7	1	price10	range300	EVFC0	year3	price20	range100	EVFC1	year0	price0	400	GASFC0
8	1	price10	range100	EVFC2	year2	price0	range300	EVFC0	year1	price10	400	GASFC1
9	1	price10	range100	EVFC1	year0	price10	range100	EVFC2	year2	price0	400	GASFC2
10	2	price10	range200	EVFC0	year1	price0	range200	EVFC0	year3	price20	400	GASFC0
11	2	price20	range100	EVFC1	year3	price10	range100	EVFC0	year2	price20	400	GASFC0
12	2	price20	range200	EVFC0	year2	price0	range200	EVFC2	year3	price0	400	GASFC2
13	2	price0	range300	EVFC2	year0	price0	range100	EVFC2	year0	price20	400	GASFC0
14	2	price0	range100	EVFC0	year1	price20	range300	EVFC0	year3	price0	400	GASFC2
15	2	price20	range300	EVFC2	year1	price0	range100	EVFC0	year0	price0	400	GASFC2
16	2	price20	range100	EVFC0	year0	price20	range300	EVFC2	year1	price20	400	GASFC0
17	2	price0	range100	EVFC1	year2	price0	range200	EVFC1	year2	price20	400	GASFC2
18	2	price0	range200	EVFC0	year3	price10	range100	EVFC2	year1	price10	400	GASFC1
19	3	price20	range100	EVFC1	year3	price0	range200	EVFC2	year0	price10	400	GASFC1
20	3	price20	range200	EVFC0	year2	price10	range100	EVFC1	year1	price20	400	GASFC2
21	3	price20	range200	EVFC2	year0	price20	range200	EVFC0	year2	price10	400	GASFC0
22	3	price20	range300	EVFC1	year1	price10	range300	EVFC1	year3	price0	400	GASFC1
23	3	price0	range200	EVFC2	year3	price20	range200	EVFC1	year2	price0	400	GASFC1
24	3	price0	range300	EVFC1	year2	price10	range300	EVFC0	year3	price10	400	GASFC0
25	3	price10	range100	EVFC0	year0	price10	range200	EVFC0	year0	price0	400	GASFC1
26	3	price10	range200	EVFC1	year1	price0	range100	EVFC1	year3	price10	400	GASFC0
27	3	price0	range100	EVFC0	year1	price10	range200	EVFC1	year0	price10	400	GASFC0
28	4	price0	range200	EVFC1	year0	price0	range100	EVFC0	year1	price0	400	GASFC1
29	4	price10	range200	EVFC2	year2	price10	range300	EVFC2	year2	price0	400	GASFC0
30	4	price10	range300	EVFC1	year3	price20	range200	EVFC0	year1	price20	400	GASFC2
31	4	price0	range200	EVFC2	year3	price10	range300	EVFC0	year0	price20	400	GASFC2
32	4	price0	range300	EVFC1	year2	price20	range200	EVFC2	year1	price0	400	GASFC0
33	4	price0	range300	EVFC0	year0	price0	range300	EVFC1	year2	price20	400	GASFC1
34	4	price0	range100	EVFC2	year1	price20	range100	EVFC2	year3	price10	400	GASFC2
35	4	price10	range300	EVFC0	year3	price0	range300	EVFC2	year2	price10	400	GASFC2
36	4	price10	range100	EVFC2	year2	price20	range100	EVFC1	year3	price20	400	GASFC1

DATA AND DESCRIPTIVE STATISTICS

The stated preference survey was administered between July 10, 2020 - August 25, 2020, to examine the aspects of free charging. A total of 4,230 panelists were invited to participate in the survey by employing a probability-based internet panel. Out of which 1,097 respondents actively engaged and completed the survey.

Out of which 250 respondents were assigned the adaptive vehicle choice SP survey and the rest were directed to complete another choice experiment on charger choice. Only the vehicle choice data was utilized for the paper. The respondents were contacted to a maximum of four times through emails with necessitated follow-up email notices. The median completion time for the survey was eleven minutes. A summary of the survey design methodology for the SP surveys is presented in Table 5.

Table 5 Survey design methodology

Time frame	*July 10, 2020 - August 25, 2020*
Target population	Civilian and non-institutional adults who are residents of the United States households (age 18 years and older)
Sampling frame	Address and demographics-based sampling by NORC
Sample designing technique	Probability and address based internet panel
Use of Interviewer	Self-administered
Mode of Administration	Self-administered via the internet
Computer Assistance	Internet-based survey
Reporting Unit	One person (age 18+) per household
Frequency	One time response collection
Levels of observation	Individual, Household
Survey designing platform	Qualtrics

The target population included civilians and non-institutional adults who are residents of the United States households (age 18 years and above). For the sampling frame, National Opinion Research Center (NORC) covered a common population of U.S adults, 18 years or older from the NORC's AmeriSpeak Panel. The sample was selected from this panel by stratifying the population by age, race/Hispanic ethnicity, education, gender, and other 44 characteristics out of a total of 48 characteristics collected in the data.

The final sample size for each sampling group was obtained by using the population distribution of the classification. Additionally, to make sure that the panel members who completed the survey were the representative sample of the target population, the expected differential survey completion rates for each demographic classification were also taken into consideration for sampling. Only one person (18 years or above) per household was eligible to participate. The period for which the sampled panelists were eligible to take the survey began on 10th of July, 2020 and ended on 25th of August, 2020.

NORC had a screening stage system that helped to locate panelists who were eligible and qualified to take the survey. A survey was marked as 'Complete' if the eligible panelist completed the survey. The sample statistics of the final weighted and unweighted sample is available in Table 6.

Post-survey adjustment was a repertoire of statistical weighting of the respondents for which NORC weighted the sample of the eligible respondents who completed the survey by using panel base sampling weights. The 'panel base sampling weights' per household were estimated as the inverse of the probability of getting selected from the NORC National Frame or the address-based sample. NORC' National Frame is the prime sampling frame from which the sample households were selected for AmeriSpeak panel.

Table 6 Sample descriptive statistics

	WEIGHTED		**UNWEIGHTED**	
	Mean	Standard	Mean	Standard
Gender				
Male	0.49	0.50	0.48	0.50
Female	0.51	0.50	0.52	0.50
Age				
18-29	0.21	0.41	0.19	0.39
30-44	0.26	0.44	0.35	0.48
45-59	0.24	0.43	0.20	0.40
60 and above	0.29	0.46	0.26	0.44
Education				
No HS diploma	0.11	0.32	0.06	0.24
HS graduate or equivalent	0.26	0.44	0.16	0.37
Some college	0.28	0.45	0.45	0.50
BA or above	0.34	0.47	0.33	0.47
Employment				
Employed Full Time	0.51	0.50	0.54	0.50
Employed Part Time	0.12	0.32	0.12	0.33
Retired	0.19	0.39	0.16	0.37
Student (and not employed for	0.04	0.20	0.03	0.18
Disabled (and not employed for	0.04	0.20	0.04	0.20
Not employed for pay	0.07	0.25	0.07	0.26
Other	0.02	0.13	0.02	0.15
Region				
New England	0.05	0.21	0.05	0.22
Mid-Atlantic	0.10	0.30	0.07	0.26
East North Central	0.16	0.36	0.16	0.37
West North Central	0.06	0.24	0.09	0.28
South Atlantic	0.21	0.41	0.18	0.38
East South Central	0.05	0.22	0.05	0.21
West South Central	0.12	0.32	0.10	0.30
Mountain	0.08	0.27	0.11	0.31
Pacific	0.18	0.39	0.20	0.40

MODELING METHODOLOGY

The panel data were first analyzed using a multinomial logit approach followed by a mixed logit (random parameters) and a latent class model. The value of free necessitated adding a dummy variable to the model for when fueling cost was zero. In statistical modeling, we use dummy variables to indicate the deficiency or attendance of some definite effect that is assumed to influence the result. Discrete choice models are adequately versatile to determine the value of free (willingness-to-pay and zero-price effect) through a ratio of coefficients. Additionally, it can determine any systematic taste variation in the value of free. The fundamental modeling approach used for the estimation was based on the random utility maximization. For any statistical model, the structural relationship between the variables and the error term (indicating the wavelength of measurement errors) plays a vital part in model performance.

For the vehicle choice experiment, each individual was assumed to have a deterministic utility for each vehicle (in this case, three vehicles, namely EV A, EV B, and a gasoline vehicle) in a decision-based conditions. The utility functions used for modeling the three given alternatives of the vehicles can be expressed as,

$$U_i = \alpha_i + \beta_p P_i + \beta_r R_i + \beta_{fc} FC_i + \beta_{f1} F_{1i} + \beta_{f2} F_{2i} + \beta_{f3} F_{3i} \ldots \tag{3}$$

where, U_i refers to the utility function for alternative I; α_i denotes the alternative-specific constants for alternative i, P_i denotes purchase price of alternative i in 1000s of dollars; R_i is the driving range of alternative i in miles; FC_i denotes the fuel cost of alternative i in 100s of dollars; F_{ti} is an indicator denoting t years of free charging bundle in alternative I; and β_p, β_r, β_{fc}, β_{f1}, β_{f2}, and β_{f3} are model parameters that are generic across the three vehicle choices.

All the discrete choice approaches used for modeling consisted of the coefficient of years of free charging attribute (β_{f1}, β_{f2}, and β_{f3}) and coefficient of purchase price variable (β_p), to capture the distribution of the zero-price effect that varies across the population. The zero-price effect or willingness-to-pay was estimated using the following formula in dollars for the stated years of free charging, t:

$$WTP_{F,t} = \frac{\frac{\partial F_{ti}}{\partial U_i}}{\frac{\partial P_i}{\partial U_X}} = \frac{\beta_{ft}}{\beta_p} \tag{4}$$

To arrive at an accurate monetary value of the zero-price effect in context of EV charging, three distinct models were estimated. First, a multinomial logit model will serve as a start point for estimating, mixed logit model and a latent class model. Second, in context of vehicle choice, two distinct models were estimated, a multinomial and a mixed logit model. Third, the monetary value of free charging will be derived from all modeling approaches and compared in both, the consumer's vehicle preference setups.

In the next section, the methodology for mixed logit model with random parameters is discussed followed by the methodology of the latent class logit model.

Mixed Logit Model and Random parameters

For standard multinomial logit results, if the disturbances are of extreme value type I, the probability of observation n having a discrete outcome denoted by i, where $i \in I$ and I refers to all the possible outcomes for n observation can be expressed as (William et al. 2020),

$$Pr_n(i) = \frac{EXP(\beta_i X_{in})}{\sum_{\forall I} EXP(\beta_i X_{in})} \tag{5}$$

A mixed logit model is an advance form of discrete choice model that can accommodate a mixing distribution. The outcome probabilities of a mixed logit model can be expressed as,

$$Pr_n^m(i) = \int_x P_n(i) f(\beta|\varphi) d\beta \tag{6}$$

where, $f(\beta|\varphi)$ is the function denoting the density of β, φ refers to a vector of parameters with the stated density function. By combining equation (5) and (6), we obtain the mixed logit

model expressed as,

$$Pr_n(i) = \frac{EXP(\beta_i X_{in})}{\sum_{\forall I} EXP(\beta_i X_{in})} f(\beta|\varphi) \tag{7}$$

The random-parameters logit approaches various limitations that the standard multinomial logit model fails to apprehend. It facilitates parameter values to vary over the observations. Random parameters are used to estimate models to avoid incorrect parameter estimates if the assumptions made while modeling are not satisfied. In the mixed logit model, the variables used as random parameters namely, free price indicator, charge time and detour time are assumed to have a normal distribution. The importance of normal distribution can be explained by the central limit theorem. It asserts that the average of given observations of a random variable (with a finite mean and variance) is a random variable with a normal distribution. The distribution grows seemingly normal as the number of observations increases. That also explains the theory behind the error term's (also referred to as measurement error) approximately normal distribution (Lyon, 2014).

Latent Class Logit model

Random parameters were used in the mixed logit model to accommodate unobserved heterogeneity. In a model specification, random parameters need a defined distribution that indicates the impact of unobserved heterogeneity on the parameter across the observations. Hence, the random parameters were assumed to have a normal distribution across the observations while estimating the mixed logit model.

Washington et al. (2020) mentioned that Ione of the many possible reasons for the unobserved heterogeneity could be that although parameters fluctuate across groups, they are fixed within the groups. On the other hand, a latent class model does not require any such assumption about the distribution. The model itself makes parametric assumptions based on observations.

However, a limitation of using the standard latent class model is that each group or class's parameters are fixed across observations. Therefore, one can choose to combine both the models and generate a latent class model with random parameters. In that, the latent classes will be identified based on respondent's decisions, and the parameters will be allowed to vary individually across the observations within every class (William et al. Chapter 17, 2020). For this project, a latent class multinomial logit model was estimated that captured the charging choice behavior in the specified model by distributing responses into appropriate classes based on the preferences. The allotment of the observations to particular classes enables the latent class model to recognize class-specific unobserved heterogeneity (Xiong and Mannering, 2013). Simultaneously, the model also accounts for heterogeneity caused due to diverse attitudinal reflexes towards free charging, amenities, demographics, and socioeconomic variables across the population in distinct classes.

The discrete choice models are expressed as a linear function of utilities U_{in} that estimates the discrete outcomes i for n observation in a system where, (see William et al. chapter 13, 17),

$$U_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{8}$$

Here, i refers to the potential discrete outcomes, β_i refers to a vector of parameters to be estimated for discrete outcome i, X_{in} indicates a vector of the identifiable characteristics that are used to estimate discrete outcomes n, and ε_{in} denotes error term that accounts for extreme-value disturbances of Type 1(McFadden, 1981) as mentioned in William et al. (2020). The outcome probabilities can be expressed as,

$$Pr_n(i|c) = \frac{EXP(\beta_{ic} X_{in})}{\sum_{\forall I} EXP(\beta_{ic} X_{in})} \tag{9}$$

where $Pr_n(i|c)$ denotes the probability of discrete outcome i, for n observation that is part of an unobserved class denoted by c (Greene and Hensher, 2003). Willian et al. (2020) determined the multinomial logit form that can be used to find the unconditional class probabilities denoted by $Pr_n(c)$, where Z_n refers to a vector of characteristics that is used to estimate the probabilities of class c for n observation, α_n is a equivalent vector of measurable parameters.

$$Pr_n(c) = \frac{EXP(\alpha_c Z_n)}{\sum_{\forall C} EXP(\alpha_c Z_n)} \tag{10}$$

As explained in Willian et al. (2020), by using the formulations provided by equation (9) and equation (10), the unrestricted probability of an individual n falling in charger choice category i can be represented as,

$$Pr_n(i) = \sum_{\forall C} Pr_n(c) \times Pr_n(i|c) \tag{11}$$

Latent class models can be promptly estimated with maximum likelihood strategies (Greene and Hensher, 2003) and (Hensher et al. 2005). The log-likelihood function can be formulated as,

$$lnL = \sum_{i=1}^{N} lnPr_i = \sum_{i=1}^{N} ln[\sum_{q=1}^{Q} H_{iq}(\prod_{t=1}^{T_i} Pr_{it|q})] \tag{12}$$

where Hiq refers to the prior probability of a class q for an individual i and $Pr_{it|q}$ denotes the probability for the particular choice of an individual i in a choice situation denoted by t | class q.

The zero-price effect and willingness-to-pay are estimated using the results from latent class model with each class having a different value of the zero-price effect based on the distribution of parameters in the respective classes.

Error Component Latent Class Model

The study also utilized an error component latent class (ECLC) model to estimate consumer preference across the three labeled alternatives: EV A, EV B, and Gasoline Vehicle. A latent class model was chosen for the analysis to account for preference heterogeneity in different membership classes. An error component latent class model captures the correlation between the EV alternatives. The general utility function for the RPLC model can be written as:

$$U_{nim} = \beta_m X_{nim} + \mu_m Z_i + \varepsilon_{nim} \tag{13}$$

U_{nim} is the utility of alternative i for individual n if in membership class m. β_m: coefficients for individual-specific alternative attributes X_{njm} in class m. μ_m is a normally distributed error component, standard deviation σ_{EV} for class m. Z_i is an indicator that alternative i is an EV. And ε_{nim} is an i.i.d. Gumbel error term.

The likelihood for the panel data where an individual n chooses alternative j in membership class m, C is the choice set inclusive of all alternatives, M_n is the number of membership class for individual n, can be expressed in the form:

$$L_{njm}(\beta) = \prod_{m=1}^{M_n} \frac{\exp\,(\beta_m X_{nim} + \mu_m Z_i)}{\sum_{j \epsilon C} \exp\,(\beta_m X_{njm} + \mu_m Z_j)} \tag{14}$$

The probability that an individual n will choose alternative j can be expressed as the integral of the product of logit probabilities for all β:

$$Pr_{nim} = \int \left[\prod_{m=1}^{M_n} \frac{\exp\,(\beta_m X_{ni} + \mu_m Z_i)}{\sum_{j \epsilon C} \exp\,(\beta_m X_{nj} + \mu_m Z_j)} \right] f(\mu) d\mu \tag{15}$$

ANALYSIS AND RESULTS

In this chapter, the effects of the purchase price, driving range, annual fuel cost, and years of free charging on free value were estimated. Two discrete choice models, namely, multinomial logit model and mixed logit were utilized. The vehicle choice experiment was divided into two components. The first one comprised of the consumer's vehicle choice where an individual got the choice of two EVs (EV A and EV B) and a gasoline vehicle whereas, the second one only gave a choice of two EVs. For every household, it was assumed that an individual decided the vehicle preference for the entire household. Table 7 displays the sample statistics of the variables that were used to generate the models for the choice of electric vehicles.

Table 7 Summary statistics for model variables for electric vehicle binary choice

Variable Description	Mean	SD	Min	Max
Purchase price of the EV (1000s of dollars)	22.24	11.82	10	72
Driving range of the EV (Miles)	193.10	81.50	100	300
Annual fuel cost of the EV (100s of dollars)	5.97	7.71	0.5	73
Two years of free charging (1 if the free charging is provided for two years, 0 otherwise)	0.22	0.41	0	1
Three years of free charging (1 if the free charging is provided for three years, 0 otherwise)	0.26	0.45	0	1

The first component estimation (Electric Vehicle Binary Choice) is discussed in the following section where an individual got the choice of two EVs: EV A and EV B.

Electric Vehicle Binary Choice

Multinomial Logit Model

The model was estimated using a statistical package called Apollo in R-Studio. Table 8 represents the results from the multinomial logit model including the model variables, its parameter estimates and t-statistics. All the variables used in the model are significant at 99% confidence level. The description follows this section, estimation results, and the conclusion of fixing the mixed logit model with random parameters for the final estimation.

Table 8 Multinomial logit estimation results for the electric vehicle binary choice

Variable Description	Estimated Parameter	*t* statistic
Constant (EV Vehicle B)	0.16	3.12
Purchase price of the EV (1000s of dollars)	-0.15	-7.98
Driving range of the EV (Miles)	0.01	20.23
Annual fuel cost of the EV (100s of dollars)	-0.10	-6.84
Two years of free charging (1 if the free charging is provided for two years, 0 otherwise)	0.77	8.19
Three years of free charging (1 if the free charging is provided for three years, 0 otherwise)	1.09	13.44
Number of individuals	258	
Number of observations	2321	
Log likelihood at zero	-1608.80	
Log likelihood at convergence	-1208.03	
McFadden ρ^2	0.25	
AIC	2428.07	
BIC	2462.57	

The first year of free charging was not included in the model as it did not generate the expected direction. Thus, the model was estimated using the two and the three years of free charging.

To test the significance of the multinomial logit model, a likelihood ratio test was performed. Two models were compared: multinomial logit model, and the mixed logit model. The equation used to perform the likelihood ratio test can be expressed as,

$$\chi^2 = -2[LL(\beta_R) - LL(\beta_U)] \tag{6.11}$$

where, $LL(\beta_R)$ is the log likelihood at convergence that utilizes the restricted betas for price and $LL(\beta_U)$ is the log likelihood at convergence that utilizes the unrestricted betas for price. The null hypothesis can be written as: The multinomial logit model and the mixed logit model are the same.

The null hypothesis was rejected with 99% confidence. Hence it was established that mixed logit approach improved the model significantly.

Mixed Logit Model (Random parameters)

The likelihood ratio test that was performed for the multinomial logit model and the mixed logit also established that mixed logit had significant random parameters confirming the presence of heterogeneity across all the individuals. Additionally, a likelihood ratio test was performed to check for the significance of any possible correlation between the random parameters, and it was found that the correlated random parameters did not improve the model significantly. Therefore, a mixed logit model with random parameters was finalized for the estimation.

The model was estimated using a statistical package called Apollo in R-Studio. Table 9 represents the results from the mixed logit model with random parameters including the model variables, parameter estimate and t-statistics. All the variables used in the model are significant at 99% confidence level with a log-likelihood of -1117.3 and an AIC of 2250.66.

Table 9 Mixed logit with random parameters results for the electric vehicle binary choice

Variable Description	Estimated Parameter	*t* statistic
Constant (EV Vehicle B)	0.18	3.03
Purchase price of the EV (1000s of dollars)	-0.21	-8.42
Driving range of the EV (Miles) (Standard deviation of parameter estimate, normally distributed, in parentheses)	0.02 (-0.01)	12.84 (-9.93)
Annual fuel cost of the EV (100s of dollars) (Standard deviation of parameter estimate, normally distributed, in parentheses)	-0.23 (0.17)	-5.60 (3.63)
Two years of free charging (1 if the free charging is provided for two years, 0 otherwise)	0.83	7.55
Three years of free charging (1 if the free charging is provided for three years, 0 otherwise)	1.34	13.44
Number of individuals	258	
Number of observations	2321	
Log likelihood at zero	-1608.80	
Log likelihood at convergence	-1117.33	
Halton Draws	1000	
McFadden ρ^2	0.31	
AIC	2250.66	
BIC	2296.65	

The purchase price of the EV induced a disutility for individuals. Since the EV market is at a developing stage, several different EV brands are sold at a much higher value of the purchase price than the purchase of the gasoline vehicles.

The driving range and the annual fuel cost of the EVs confirmed the presence of significant random parameters, and the attributes were assumed to be normally distributed. It also indicated that individuals preferred EVs with a higher driving range. The driving range of EVs induced a utility for the individuals, which can be explained by the higher and improved range of EVs as contrasted to any other type of vehicle. Another possible explanation can be that it reduced the need to repeatedly stop for charging the EV and thus increased their travel time by a considerable amount. However, the annual cost of the EVs induced a disutility for individuals.

The parameters indicating free charging years, two years of free charging, and three years of free charging, both induced utility for individuals. The parameter indicating three years of free charging generated a higher utility than the two years of free charging parameter. This established that individuals attended free charging at positive value (see section 9 for the estimated WTP).

The second component estimation (Electric and Conventional Vehicle Choice) is discussed in the following section where an individual got the choice of two EVs and a gasoline vehicle.

Electric and Conventional Vehicle Choice

Table 10 displays the sample statistics of the variables that were used to generate the models and the results.

Table 10 Summary statistics of model variables for electric and conventional vehicle choice

Variable Description	Mean	SD	Min	Max
Purchase price of the vehicle (1000s of dollars)	22.25	11.82	10	72
Driving range of the vehicle (Miles)	266.00	81.54	100	400
Annual fuel cost of the vehicle (100s of dollars)	7.18	7.69	0.5	73
Two years of free charging (1 if the free charging is provided for two years, 0 otherwise)	0.22	0.41	0	1
Three years of free charging (1 if the free charging is provided for three years, 0 otherwise)	0.26	0.45	0	1

Multinomial Logit Model

The model was estimated using a statistical package called Apollo in R-Studio. Table 11 represents the results from the multinomial logit model including the model variables, its parameter estimates and t-statistics. All the variables used in the model are significant at 99% confidence level. The description and estimation results follow this section and the explanation for concluding the mixed logit model with random parameters for the final estimation. Since it is a labeled experiment, the alternative specific constants were fixed for both the EVs (EV A and EV B), allowing for the estimation of the gasoline vehicle's alternative specific constant.

Table 11 Multinomial logit estimation results for the electric & conventional vehicle choice

Variable Description	Estimated Parameter	t statistic
Constant (Gasoline Vehicle)	-0.62	-6.46
Purchase price of the vehicle (1000s of dollars)	-0.07	-5.16
Driving range of the vehicle (Miles)	0.01	17.65
Annual fuel cost of the vehicle (100s of dollars)	-0.02	-3.46
Two years of free charging for EVs (1 if the free charging is provided for two years, 0 otherwise)	0.35	3.78
Three years of free charging for EVs (1 if the free charging is provided for three years, 0 otherwise)	0.53	6.73
Number of individuals	258	
Number of observations	2311	
Log likelihood at zero	-2538.89	
Log likelihood at convergence	-2266.40	
McFadden ρ^2	0.11	
AIC	4544.79	
BIC	4579.26	

The first year of free charging was not included in the model as it did not generate the expected direction. Thus, the model was estimated using the two and three years of free charging.

To test the significance of the multinomial and the mixed logit model in this case, a similar likelihood ratio test was performed. Two models were analyzed; the multinomial logit model and the mixed logit model, with a conclusion that the mixed logit approach improved the model significantly with 99% confidence.

Mixed Logit Model (Random parameters)

The finding from the likelihood ratio test also established that mixed logit had significant random parameters validating the existence of heterogeneity across all the individuals.

Additionally, a likelihood ratio test was performed to check for the significance of any potential correlation between the random parameters and it was found that the correlated random parameters did not improve the model significantly. Therefore, a mixed logit model with random parameters was finalized for the estimation.

The model was estimated using the same statistical package called Apollo in R-Studio. Table 12 represents the results from the mixed logit model with random parameters including the model variables, parameter estimate and t-statistics. All the variables used in the model are significant at 99% confidence level with a log-likelihood of -1557.65 and an AIC of 3131.31.

Table 12 Mixed logit results for the electric and conventional vehicle choice

Variable Description	Estimated Parameter	*t* statistic
Constant (Gasoline Vehicle)	3.12	15.21
Purchase price of the vehicle (1000s of dollars)	-0.15	-6.56
Driving range of the vehicle (Miles) (Standard deviation of parameter estimate, normally distributed, in parentheses)	0.01 (0.02)	5.63 (10.17)
Annual fuel cost of the vehicle (100s of dollars) (Standard deviation of parameter estimate, normally distributed, in parentheses)	-0.19 (0.34)	-5.28 (5.43)
Two years of free charging for EVs (1 if the free charging is provided for two years, 0 otherwise)	0.63	4.83
Three years of free charging for EVs (1 if the free charging is provided for three years, 0 otherwise)	0.96	8.72
Number of individuals	258	
Number of observations	2311	
Log likelihood at zero	-2538.89	
Log likelihood at convergence	-1557.65	
Halton Draws	1000	
McFadden ρ^2	0.39	
AIC	3131.31	
BIC	3177.27	

The purchase price of the vehicle induced a disutility for individuals. The driving range and the annual fuel cost of the EVs established the presence of significant random parameters, and the attributes were considered to be normally distributed. The driving range of vehicles induced a utility for the individuals. The indicated that individuals prefer vehicles with a higher driving range as it reduces their dependence on the fuel and the need to repeatedly stop for fueling the vehicle and thus increasing their travel time. The annual cost of the vehicles induced a disutility for individuals. The annual fuel cost of gasoline vehicles is much higher than that of the EVs, and hence it can be concluded that the disutility is rational in occurrence.

The parameters indicating free charging years for EVs, namely, two years of free charging, and three years of free charging, both induced utility for individuals. Similar to the result of the mixed logit with random parameters for the choice of EVs, the parameter indicating three years of free charging for this model generated a higher utility than the two years of free charging parameter. This established that individuals valued free charging at positive range.

It should be recorded that since gasoline vehicles do not have any free charging elements, the utility function did not include any parameter or coefficient for free charging years.

In the next section, the distribution of the zero-price effect is discussed with respect to the charger and the vehicle choice.

Distribution of the Zero-Price Effect

Table 13 presents a distribution of ZPE from two years of free charging, ZPE from three years of free charging and value of range across the United States residents who are 18 years and above for the vehicle choice experiment with the corresponding log-likelihood, the estimated AIC and BIC.

Table 13 Vehicle choice distribution for the value of free

Model	LL	AIC	BIC	K	ZPE (2 years)	ZPE (3 years)	Value of Range
Electric Vehicle Binary Choice							
MNL	-1208.03	2428.07	2462.57	6	-$5133	-$7266.67	-$66.67
Mixed Logit (Random parameters)	-1117.3	2250.66	2296.65	12	-$3952	(Mean) -$4708.92 (SD) -$3031.11	-$62.25 -$39.64
Electric and Conventional Vehicle Choice							
MNL	-2266.395	4544.79	4579.26	7	-$5000	-$7571	-$143
Mixed Logit (Random parameters)	-1557.6	3131.31	3177.27	13	-$4200	(Mean) -$6318.55 (SD) -$4579.65	-$48.66 -$44.79

The zero-price effect (ZPE) was calculated separately for the free charging provided for two years and three years. For one year, the free charging period was not used in the model as it did not improve the log-likelihood significantly. It was also separated by the two components of the vehicle choice experiment.

The ZPE obtained signified the price that the individuals assumed they got profited by receiving two or three years of free charging. The ZPE is the price that they would have to pay to charge their EVs for the stated number of years if they did not have free charging for those years.

For the component representing the electric vehicle binary choice, the highest ZPE for two years of free charging was generated by the multinomial logit model (MNL) priced at -$5133 for two years. However, the distribution can be explained better by using a mixed logit model with random parameters as it significantly improved the model. The ZPE generated by the mixed logit model with random parameters was priced at -$3952 for two years of free charging. Similarly, the basic MNL produced the higher ZPE for three years of free charging priced at --$7266.67, and the mixed logit with random parameters produced a ZPE with a mean of -$4708.92 and a standard deviation of -$3031.11.

The component representing two EVs and gasoline vehicles' choice established a ZPE of -$5000 and -$4200 for the MNL and the mixed logit with random parameters, respectively, for two years of free charging. The three years of free charging generated a ZPE of -\$7571 using the MNL and a ZPE with a mean of -\$6318.55and a standard deviation of -\$4579.65 by utilizing a mixed logit model with random parameters.

The value of the range was estimated for both the components of the vehicle choice experiment. The WTP for the driving range by the Dimitropoulos et al. (2013) was based on the reviews of around 30 past pieces of research about the value of the driving range. The WTP for a marginal increase in the driving range can be expressed as the ratio of the marginal utilities of the driving range and the purchase price:

$$WTP_{Range} = \frac{-(\partial U_i/\partial R_x)}{(\partial U_i/\partial P_x)}, \tag{9.1}$$

where R represents the driving range of the vehicle, P is an indicator of the purchase price and U is an individual's stochastic utility function.

The value of the range is termed variously by researchers such as 'WTP for increased range' in Greene et al. (2020) and 'WTP to pay for driving range' in Dimitropoulos et al. (2013). A comprehensive review of the past literature on the value of range was presented in Greene et al. (2020) stating that the mean WTP for increased range from Dimitropoulos et al. (2013) was assessed at \$67 per mile of the range. Additionally, Greene et al. (2017) valued the WTP for the increased range at \$90 per mile traveled.

Considering the Electric vehicle binary choice experiment, the value of range was estimated sing equation (9.1) at \$66 per mile using the MNL and -\$62.25 (Mean) and -\$39.64 (Standard deviation) using the mixed logit with random parameters. The value of the range was calculated at -\$48.66 (Mean) and -\$44.79 (Standard deviation) using the mixed logit and, \$143 per mile using the MNL for the Electric and Conventional Vehicle Choice. The WTP for the driving range, confirmed with the valued obtained from the last research.

It should be remarked that the computations are based on Bayesian estimation from Greene (2004). The ZPE values were evaluated concerning individual-level parameters for the parameters that were discovered to be random (varying across individual).

Error Component Latent Class Model

An exploratory latent class approach was employed initially where the number of classes was chosen depending on sample-adjusted BIC. The five class models had best performance with a SABIC of 2619 as compared to the four- and six-class models (SABICs of 2636 and 2631 respectively). When looking at the significance of parameter estimates within the classes, the modelers noticed that the classes generally fit a pattern of attribute non-attendance. For parsimonious and interpretative reasons, restricted models of attribute non-attendance were estimated and are presented in Table 14.

The first class exhibits insensitivity to the electric vehicle options. A significant proportion of respondent showed no interest in EVs as evidenced by choosing the conventional vehicle option across all scenarios. The Conventional Only class accounted for approximately 33% of the weighted sample.

The second class are individuals who are insensitive to free charging. This group was approximately 5 percent of the population. Individuals in this group exhibited a willingness to pay (WTP) for 1 miles of range of approximately \$662. This is due to the very small and insignificant sensitivity to cost.

Classes three through five include people of varying attentiveness to free charging. The third class included individuals who preferred at least three years of free charging. This group was approximately 15% of the population. Their WTP for a 3-year free charging bundle was \$4,710. Individuals in this group exhibited a WTP for 1 mile of range of approximately \$248.

The fourth class included individuals who preferred at least two years of free charging. This group was approximately 12% of the population. Their WTP for a 3-year free charging bundle was \$4,230, while their WTP for two years was \$2,205. Individuals in this group exhibited a WTP for 1 miles of range of approximately \$19. This group was less sensitive to cost than classes 3 and 5.

The fifth class included individuals who were interested in free charging bundles of one, two, and three years in length. This group was approximately 36% of the population. Their WTP for a free charging bundle was \$2,992 for one year, \$4,814 for two years, and \$9,065 for three years. Individuals in this group exhibited a WTP for 1 miles of range of approximately \$112.

The parameter estimates along with the ZPE and value of range for all the classes is displayed in Table 14.

Table 14 Error component latent class results for the electric & conventional vehicle choice

Variable	Class 1: Conventional Only		Class 2: Inattentive Free Charging		Class 3: 3 Years Free Charging		Class 4: 2+ Years Free Charging		Class 5: Fully Attentive Free Charging	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant (Electric Vehicle B)	-0.67	-1.69	1.38	4.71	0.65	1.49	-0.13	-0.30	0.27	1.58
Constant (Gasoline Vehicle)	10.55	18.57	1.56	3.55	9.60	3.08	-12.04	-1.46	5.81	7.71
Purchase price ($1000)	0.00	.	0.00	-0.05	-0.22	-1.87	-1.23	-2.26	-0.16	-3.89
Driving range (100-mi) [EV Only]	0.00	.	0.31	1.90	5.54	3.55	2.30	2.75	1.75	6.99
Annual fuel cost ($100) [All Alts]	0.00	.	-0.54	-2.14	-3.93	-4.42	-1.08	-2.72	-0.16	-4.19
One-year free charging indicator	0.00	.	0.00	.	0.00	.	0.00	.	0.47	1.23
Two years free charging indicator	0.00	.	0.00	.	0.00	.	2.72	2.77	0.75	1.80
Three years free charging indicator	0.00	.	0.00	.	1.05	1.57	5.22	2.19	1.42	3.68
Variance of EV Error Component	10.42	13.76	0.00	.	11.45	3.26	22.00	2.52	1.90	3.57
Class probability	0.3296		0.0477		0.1453		0.1186		0.3588	
WTP: 1 year of free charging ($)	--		--		--		--		$2,992	
WTP: 2 years of free charging ($)	--		--		--		$2,205		$4,814	
WTP: 3 years of free charging ($)	--		--		$4,710		$4,230		$9,065	
WTP: EV range ($/mi)	--		$662		$248		$19		$112	
Number of Individuals	250									
Number of Observations	2250									
Number of Parameters	36									
Log-likelihood (constants only)	-2326.67									
Log-likelihood at convergence	-1271.86									
McFadden ρ^2	0.45									
Sample-Adjusted BIC	2628.38									

CONCLUSIONS AND POLICY IMPLICATIONS

Using a representative sample of 250 individuals from the US, the project proposed finding out the potential consumer 'value of free charging' as a function of dollars per charging event, exclusively for public charging infrastructures, by employing an adaptive labelled stated preference (SP) survey and a mixed logit model. Results from latent class discrete choice models showed heterogeneity in the sensitivity to free charging time scale (at two to three years) with a significant share of the population showing no sensitivity to a single year of free charging. Respondents valued free charging between about \$1100 to \$3000 per year depending on class (attentiveness to free charging). A significant proportion of the population showed no interest in electric vehicles. By using a latent class formulation, this group can be explicitly accounted for thus leading to less bias in estimating willingness-to-pay for EV attributes.

This study did not include socio-demographics in the model specifications. This was chosen due to the study's focus on policy and measurement rather than behavioral explanation. For early analysis of free charging policies and pricing structures, the cost-effectiveness of the policy is a greater focus than the exact structure of the policy, so a looser mean-focus and distribution-focused approach brings greater value. Future work can look at the demographic characteristics of the preference classes. This allows for tailoring the policies and business plan around groups that may see greater benefit from the program or groups most likely to use chargers from companies that offer free charging in some form. Understanding the demographic also may have implication for equity analysis.

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