

## **A Random Parameters Latent Class Analysis to Estimate the Value of Free Charging Bundle in Electric Vehicle Purchases**

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### **SUMMARY**

Although there has been a sudden surge of interest in the Electric Vehicle (EV) market due to climate change and sustainability concerns, their regular users are still a minority. As policymakers and businesses consider expanding EV infrastructure and updating the pricing structures to increase EV demand, there is limited guidance on the value that consumers place on free charging. 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. This paper finds willingness-to-pay for free charging bundles that range from about \$1100/year to \$3000/year which is well below the average cost of EV fueling (~\$500) and conventional vehicle fueling (~\$1200) in the United States.

**Keywords:** Vehicle Preference, Stated Preference, Choice Experiment, Charging Policy

### **1. INTRODUCTION**

Local, regional, and national government internationally are currently analyzing, proposing, and executing policies to encourage electric vehicle (EV) adoption. For example, the United States Department of Energy claims that utilizing EVs can significantly enhance nations' energy security and decrease greenhouse gas emissions (USDOE, 2020). But EV market share still significantly trails conventional vehicles. 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). McMahan (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 ( $\approx 1575$  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.

This study establishes a national estimate of the willingness-to-pay (WTP) for a free charging bundle in the United States electric vehicle market. This willingness-to-pay provides an estimate of the additional value placed on the free charging bundle versus charging cost discount. Using an adaptive stated choice experiment conducted using a probability-based sample from an internet panel, 36 choice scenarios were generated with 9 scenarios received per respondent. 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.

## 2. METHODOLOGY

### *Survey Design*

A total of 4,230 panelists were invited to participate in the survey by employing a probability-based internet panel and 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. A summary of the survey design methodology is presented in Table 1.

**Table 1: Survey Design Methodology**

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

The survey gathered information about respondents' household characteristics, commutes, vehicles, and socio-demographic factors in addition to the SP questions.

The choice design was generated using Ngene. The final design of the choice experiment had 36 scenarios distributed over 4 blocks. Each respondent was presented with only 1 block (9 scenarios). The choice experiment included four attributes: *purchase price*, *driving range*, *annual fuel cost* and *years of free charging*. Price and annual fuel cost were adaptive attributes. Driving range varied for EVs but was constant for conventional vehicles. Years of free charging only varied for EV alternatives.

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. The mileage was then used to adapt the fuel cost based on the fuel economy levels. Equations 1-2 summarize how annual fuel cost was calculated.

$$Annual\ Fuel\ Cost_{GAS} = Distance\ covered\ in\ 1year\ (mi) \times Fuel\ Price\ \left(\frac{\$2.5}{USGal}\right) \times Fuel\ Consumption\ \left(\frac{USGal}{mi}\right) \quad (1)$$

$$Annual\ Fuel\ Cost_{EV} = Distance\ covered\ in\ 1year\ (mi) \times Fuel\ Price\ \left(\frac{\$0.13}{kWh}\right) \times Fuel\ Consumption\ \left(\frac{33.7\ kWh}{mi}\right) \quad (2)$$

This was followed by basic definitions of an EV and a short explanation of attributes used in the SP scenario. It was followed by the SP section, where 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 EVs and one conventional gasoline vehicle) with varying characteristics (Figure 1).


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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

**Figure 1: An Example Scenario**

**Table 2: Attributes Levels**

Attribute	Levels	
<b>Purchase price</b> (relative to your future vehicle choice)	Same, 10% higher, 20% higher	
<b>Driving range</b> (EV only)	100 miles, 200 miles, 300 miles	
<b>Annual fuel cost</b> (adapted by vehicle drivetrain and size)	EV	Gasoline
	Low, Medium, High	Low, Medium, High
<b>Years of free charging</b> (EV only)	0-year, 1 year, 2 years, 3 years	

**Modeling Methodology**

The study utilized a random parameters latent class (RPLC) model (Green and Hensher, 2012) 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 in Equation 3:

$$U_{nim} = \beta_m X_{nim} + \mu_m Z_i + \varepsilon_{nim} \quad (3)$$

where,

$U_{nim}$  is the utility of  $n$  individuals who selected alternative  $i$  in membership class  $m$ ,  
 $\beta_m$  are the coefficients corresponding to individual-specific alternative attributes  $X_{njm}$  in class  $m$ ,

$\mu_m$  is a normally distributed error component with standard deviation  $\sigma_{EV}$  for class  $m$ ,

$Z_i$  is an indicator that alternative  $i$  is an EV, and

$\varepsilon_{nim}$  is an 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 of Equation 4:

$$L_{njm}(\beta) = \prod_{m=1}^{M_n} \frac{\exp(\beta_m X_{nim} + \mu_m Z_i)}{\sum_{j \in C} \exp(\beta_m X_{njm} + \mu_m Z_j)} \quad (4)$$

The probability that an individual  $n$  will choose alternative  $j$  can be expressed as the integral of the product of logit probabilities for all  $\beta$  as in Equation 5 (Maness:

$$P_{njm} = \int \left[ \prod_{m=1}^{M_n} \frac{\exp(\beta_m X_{ni} + \mu_m Z_i)}{\sum_{j \in C} \exp(\beta_m X_{nj} + \mu_m Z_j)} \right] f(\beta) d\beta \quad (5)$$

**3. RESULTS AND DISCUSSION**

The collected sample was weighted according to US population statistics and had the following descriptive statistics:

**Table 3: Sample Descriptive Statistics**

Description	Levels	Weighted		Unweighted	
		Mean	SD	Mean	SD
Gender	Male	0.50	0.50	0.55	0.50
	Female	0.50	0.50	0.45	0.50
Age	18-29	0.22	0.41	0.19	0.39
	30-44	0.21	0.41	0.30	0.46
	45-59	0.27	0.45	0.24	0.42
	60 and above	0.30	0.46	0.27	0.45
Education	No HS diploma	0.08	0.28	0.03	0.18
	HS graduate or equivalent	0.27	0.44	0.21	0.41
	Some college	0.29	0.45	0.44	0.50
	BA or above	0.37	0.48	0.32	0.47
Employment	Employed full time	0.54	0.50	0.55	0.50
	Employed part time	0.09	0.29	0.10	0.30
	Retired	0.01	0.09	0.02	0.13
	Student (and not employed for pay)	0.07	0.26	0.06	0.24
	Disabled (and not employed for pay)	0.16	0.37	0.13	0.34
	Not employed for pay	0.04	0.20	0.06	0.24
	Other	0.08	0.27	0.07	0.26
Region	New England	0.05	0.22	0.06	0.24
	Mid-Atlantic	0.13	0.34	0.15	0.36
	East North Central	0.14	0.35	0.13	0.34
	West North Central	0.06	0.24	0.08	0.27
	South Atlantic	0.20	0.40	0.15	0.36
	East South Central	0.05	0.23	0.08	0.27
	West South Central	0.12	0.33	0.12	0.33
	Mountain Pacific	0.08 0.16	0.28 0.37	0.09 0.14	0.28 0.35
Metro/ Non-Metro	Metro area	0.83	0.37	0.85	0.36
	Non-Metro area	0.17	0.37	0.15	0.36
Driven EV/ Not driven EV	Driven EV	0.19	0.39	0.16	0.37
	Not driven EV	0.80	0.40	0.84	0.37
Household size	1	0.16	0.37	0.16	0.37
	2	0.34	0.48	0.33	0.47
	3	0.14	0.35	0.18	0.38
	4	0.10	0.30	0.11	0.32
	5	0.08	0.27	0.07	0.25
	6	0.18	0.38	0.15	0.36
Household annual income	Less than or equal to \$25,000	0.18	0.39	0.22	0.41
	\$25,001-\$50,000	0.23	0.42	0.23	0.42
	\$50,001-\$100,000	0.34	0.48	0.34	0.47
	\$100,001-\$200,000	0.19	0.39	0.18	0.38
	More than \$200,000	0.06	0.24	0.04	0.20

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 here.

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.

**Table 4: Mixed Latent Class Model Results**

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 $\rho^2$	0.45									
Sample-Adjusted BIC	2628.38									

#### 4. CONCLUSIONS

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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