How Does Charging Network Design Affect Electric Vehicle Adoption?

FINAL PROJECT REPORT

by

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16. Abstract

The used car market is a critical element of the mass adoption of electric vehicles (EVs). However, most previous studies on EV adoption have focused only on new car markets. This report examines and compares the effects of charging infrastructure characteristics on preferences for electric vehicles among both new and used car buyers. This study used an online stated preference choice experiment involving private car owners in the U.S. Two separate latent class models with three classes each were built for used and new car buyers. The latent class model suggested that different groups of car buyers respond to different types of EV charging infrastructure. In addition, a detailed analysis of EV and charging infrastructure characteristics was conducted to support the roll-out of EVs. The results of this work can be applied to quantify the tradeoffs between different types of investments in charging infrastructure. For example, the models can be used to determine the factors that have the greatest effects on purchase choices: neighborhood slow charging stations near homes and workplaces, in-town fast charging stations, highway corridor fast charging, and conventional fast-charging versus extreme-fast-charging.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
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EXECUTIVE SUMMARY

It has been almost a decade since the first release of commercially available electric vehicles (EVs) in 2010, and as more early adopters sell and replace their EVs, the used market for EVs will expand. However, most previous studies have focused on new car buyers and new EV markets, while less attention has been paid to used EV adoption and secondary EV markets.

This study conducted a choice experiment set in a context in which respondents are buying their next personal car. Before the choice experiment, respondents answered questions about their socio-economic background and their preferences for a new car or a used car for next car purchase, and then they were directed to scenarios of new car options or used car options accordingly. The choice tasks designed in this study provided two purchase options, a conventional car powered by gasoline and an electric version of the conventional car, identical in all ways except that it would run solely on electricity. While existing studies have shown that financial, technical, infrastructure, and policy attributes all affect consumers' preferences for EVs, this study focused on attributes of the EV and the charging infrastructure. Key attributes included in the study were purchase price, driving range, walking distance of the nearest slow charging options to home and to work, fast charging time, fast charging availability in town, and fast charging availability on the highway.

The online stated preference choice experiment collected data from 983 private car owners in the U.S. Each respondent was randomly assigned to six of the 240 tasks generated by using an orthogonal design. To identify how preferences for EVs differed between new car and used car buyers, we estimated separate choice models for used car buyers and new car buyers. Then a latent class logit model was chosen as the best model for further analysis. The latent class model suggested that different groups of car buyers responded to different types of EV charging infrastructure. The largest groups were found to respond to having fast charging stations available in town, and to having shorter walking access from charging stations to home and work. Smaller groups of both used and new car buyers were found to be more sensitive to fast charging time and to the spacing of fast charging stations along the highway.

After the choice model had been built, a sensitivity analysis was conducted to examine how the vehicle choices of respondents varied with changes in different predictor variables. Then the effects of varying different attributes—including characteristics of EVs and charging infrastructure as well as trade-offs among those characteristics—on the probability of buying new and used EVs rather than buying new and used gasoline cars were examined and compared in several scenarios while other predictors are assigned consistent values in all the scenarios.

The results of this work can be applied to quantify the tradeoffs among different types of investments in charging infrastructure. For example, the models can be used to determine what factors will have the greatest effects on purchase choices: neighborhood slow charging near homes and workplaces, in-town fast charging stations, highway corridor fast charging, and conventional fast charging versus extreme fast charging.

CHAPTER 1. Introduction

Many jurisdictions worldwide have set ambitious goals for continued growth and mass adoption of electric vehicles (EVs), and significant new public and private investments in expanding EV markets are expected. To sustain market growth, EVs must be practical and attractive not only to new car buyers but also to used car buyers. It is generally accepted that the relative attractiveness of EVs and other alternative fuel vehicles (AFVs) depends on several factors. These include up-front cost, operating costs including fuel (electricity) and maintenance, range, refueling/recharging time, the availability of refueling infrastructure, environmental impacts, and government incentives, as well as those factors that affect any vehicle purchase decision, such as vehicle size, performance, and features (Hoen and Koetse, 2014; Tanaka et al., 2014; Coffman et al., 2017; Liao et al., 2017). In the case of EVs, many of these factors are determined by the characteristics of the charging infrastructure, i.e., the number, type, locations, and pricing of charging stations.

Because charging infrastructure has a significant effect on the adoption of electric vehicles, previous research has generally indicated that to make EVs more attractive to consumers, we should make charging opportunities ubiquitous, fast, and inexpensive. However, in a world with budget constraints, tradeoffs must be made among these goals. Fortunately, many charging needs can be satisfied through relatively inexpensive level 1 and level 2 charging points at homes, workplaces, and other intra-city locations (TRB and National Research Council, 2015). Although they serve relatively few charging events, expensive, high power direct current fast charging (DCFC) and extreme fast charging (XFC) stations are a key to making EVs feasible for longer, interurban trips, which will be necessary for EVs to attract mainstream consumers (Fontaine, 2008; Botsford and Szczepanek, 2009; Jabbari et al., 2018).

Home and workplace charging are found to be the most frequently used and the most influential charging infrastructure that encourages consumers to purchase an EV (Dunckley and Tal, 2016; Hardman et al., 2018). Beyond private charging, Axsen and Kurani (2013) suggested that the installation of public charging infrastructure may alleviate some of the functional concerns of car buyers. Neaimeh et al. (2017) found that fast chargers enabled battery electric vehicles (BEVs) to be used on journeys above their single-charge range, which would have been impractical using regular slow chargers. This suggests that fast chargers could help overcome perceived and actual range barriers, making BEVs more attractive to future users. While consumer preferences for EVs and EV charging infrastructure have been broadly studied previously, there is little consensus on how to direct investments to achieve the greatest public benefit per dollar spent on new charging infrastructure. Hardman et al. (2018) further indicated that in some areas of study, the literature is not sufficiently mature to draw any conclusions and suggested that more research is especially desired to determine how much infrastructure is needed to support the roll-out of EVs.

Another issue is that it has been almost a decade since the first release of commercially available EVs in 2010, and as more early adopters sell and replace their EVs, the used market for EVs will expand. However, most previous studies have focused on new car buyers and new EV markets, while less attention has been paid to used EV adoption and secondary EV markets. A study in the Netherlands showed that secondhand AFV buyers are roughly twice as price-sensitive as new AFV buyers, while preferences for other attribute levels, including driving range, charging time, and detour time for charging, are very comparable between buyers of new and secondhand cars (Hoen and Koetse, 2014). A study examining the status of the nascent secondary EV market in California showed that short-range used EV owners were charging their vehicles less than they could, and early used EV buyers had significant knowledge gaps, such as being unaware of new EV purchase incentives, which reduced their ability to compare price options (Tal et al., 2017).

According to an Edmunds report (Edmunds, 2019a, 2019b), nearly 70 percent of all U.S. vehicle sales in 2018 were for used vehicles. Therefore, used EV sales have the potential to be very significant in the market as a whole (Tal et al., 2017). To reach the goal of mass adoption of EVs, the used car market will be a critical target. To shift used car buyers toward used EVs, it will be necessary to understand used car buyers' preferences for and concerns about used EVs. Used car buyers are more likely to be low-income people who cannot afford a brand new EV, and garage orphans who do not have off-street home parking space or accessible electricity outlets for home charging (Seattle Office of Sustainability and Environment, 2014). Used EVs tend to be less expensive and so would be favored by potential used car buyers who want to adopt new technology at an affordable price, but the barrier of charging, especially home charging, still exists in most cases. Nevertheless, how the availability of charging infrastructure affects used car buyer's preference for used EVs and how those effects are different than for new car buyers have been rarely investigated in previous studies.

To fill in the gaps, this study conducted a stated preference choice experiment among new car buyers and used car buyers in the U.S. via an online survey to examine the effects of charging infrastructure characteristics on preferences for EVs. This study further attempted to provide potential charging solutions to encouraging garage orphans to adopt EVs. This study contributes to the existing literature in several ways. First, it is one of the earliest nationwide investigations of preferences for used EVs in the U.S., which could provide a more comprehensive analysis and a broader insight into EV adoption. Second, this study reduced the choice burden of respondents by providing two purchase options, a conventional car versus an EV, allowing for the collection of better quality data and more accurate model results. Third, this study focused on charging infrastructure in more detail, including location, type, and charging duration, enabling a more reliable inference of the effects of charging infrastructure characteristics on EV adoption, and these could function as a reference for charging network design and infrastructure planning.

The rest of the report is organized as follows. The next section explains the survey design and the data collection process, including the attributes and attribute levels used in our choice experiment. Data analysis and model results are presented in the results and analysis section. The final section discusses findings and summarizes the report with potential suggestions for future studies.

CHAPTER 2. Survey Design and Data Collection

The choice experiment of this study was set in a context in which respondents were buying their next personal car. Before the choice experiment, respondents answered questions about their socio-economic background and were asked about their preferences for a new car or a used car for next car purchase, and then they were directed to scenarios of new car options or used car options accordingly.

The choice tasks designed in this study provided two purchase options, a conventional car powered by gasoline, and an electric version—assuming everything else identical—of the conventional car, which ran solely on electricity. While existing studies have shown that financial, technical, infrastructure, and policy attributes all affect consumers' preferences for EVs, this study focused on attributes of the EV and the charging infrastructure. Key attributes included in the study were purchase price, driving range, walking distance of the nearest slow charging options to home and to work, fast charging time, fast charging availability in town, and fast charging availability on highway. The gasoline car option was the reference alternative, with all attribute levels fixed throughout the entire experiment. All attributes and levels of the choice experiment are summarized in table 2.1.

To avoid situations in which the car purchase prices were too high for respondents to afford to buy, resulting in ineffective detection of the effects of other attributes on preferences, respondents were asked about the anticipated highest amount of money they would spend on their next car purchase, for which they were provided a choice of eight price categories in a drop-down menu. Purchase prices in the choice experiment were pivoted around this maximum price, and prices would never exceed a respondent’s selected budget limit.

Table 2.1 Attribute levels used in the choice experiment

Attribute	Alternative	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7
Price (US Dollar)	Gasoline car	0.85 *budget[1]						
	EV	1.0 *budget	0.85 *budget	0.7 *budget				
Fuel Cost (Per 100 Miles)	Gasoline car	$12						
	EV	$4						
Driving Range (Miles)	Gasoline car	400						
	EV	400	300	200	100			
Slow Charging to Home (Minutes)	EV	0	1	2	3	5	10	20
Slow Charging to Work (Minutes)	EV	0	1	2	3	5	10	20
Fast Charging Time	EV	5min	15 min	30 min	1h			
Fast Charging Density in Town	EV	5min	10 min	15 min	Not available			
Highway Fast Charging Spacing (Miles)	EV	30	50	70	Not available			

1 Respondent's anticipated highest amount of money they would spend on their next car purchase

Driving range is one of the most important attributes of an EV and is very much likely to be related to car buyers' demand for charging infrastructure. According to the driving range of current EV models in the market, and considering prospects for continued improvements in battery technology, this choice experiment varied the driving range of the EV from 100 miles to 400 miles while keeping the driving range of the gasoline car fixed at 400 miles.

Charging infrastructure availability in previous work has been operationalized as refueling distance, additional detour time beyond that needed to reach a gas station, percentage of the number of gas stations, and presence in common destinations (Chorus et al., 2013; Hoen and Koetse, 2014; Jensen et al. 2013, Tanaka et al., 2014; Valeri and Danielis, 2015). However, those measures are not conducive to providing specific implications to decision-makers for infrastructure investment (Liao et al., 2018). While Liao et al. (2018) tried to address this by noting the different distributions of charging stations in urban areas and on highways, they only specified fast charging stations and excluded slow charging options in their study. Therefore, this study included both slow charging and fast charging solutions to enable policymakers to understand tradeoffs between investments in these different charging solutions.

Slow charging availability was presented as the walking distance (in minutes) to a charging point from home and from work. We assumed car owners would park their EV at a nearby slow charging station and then walk back home or to work while waiting for a slow charge. The choice experiment also explained to respondents that it normally takes 4 to 10 hours to charge an electric car from empty to full using slow charging.

Similar to Liao et al. (2018), fast charging options were shown in terms of in-town density and highway spacing. In-town density was specified as the driving distance to a fast charging station from any place in town, while highway spacing was specified as the distance between consecutive fast charging stations along the highway. In this way, an optimal charging infrastructure distribution for both slow versus fast charging, and in-town versus highway could be estimated.

On top of location and density of fast charging, fast charging time was also shown in the choice tasks. Previous studies (Chorus et al., 2013; Hackbarth and Madlener, 2013) have not distinguished between slow and fast charging and have applied a wide range of charging times (usually 10 minutes to 8 hours). Rarely have they investigated the impacts of a shorter charging time, where most of them have a lower bound of 10 minutes for a full charge. Therefore, given that extreme fast charging has made great technical progress, this study applied fast charging times ranging from 5 minutes to 1 hour, aiming to enable a more reliable inference of the effects of reduced charging time on EV adoption and to anticipate the benefits of advanced fast charging technologies.

The choice tasks were generated by using an orthogonal design with 240 fractional factorial scenarios extracted from the full factorial combinations. Each respondent was randomly assigned to six of the 240 tasks. Figure 2.1 shows an example of a choice scenario for a respondent who preferred to buy a used car and would spend at most $20,000 for his or her next personal car purchase.

The survey was designed and implemented in SurveyMonkey, an online survey tool, and was distributed through Amazon Mechanical Turk (MTurk), a crowdsourcing system that has become increasingly popular as a tool for research, as the working population is found to be diverse across several notable demographic dimensions such as age, gender, and income (Ross et al., 2010). Recruited respondents were qualified as car owners who have completed 100 tasks on MTurk with a minimum 95 percent acceptance rate, and were sampled in proportion to population in the four time zones in the U.S. Data collection was conducted from June 28 to July 9, 2019, and overall, 983 respondents completed the full survey with valid responses. Table 2.2 summarizes the socio-demographics and basic characteristics of parking situation and personal car usage of the sample. Table 2.2 also presents socio-demographic characteristics of the U.S. population reported by the American Community Survey 2017 (five-year estimates) for comparison.

Option	Used Gasoline Car	Used EV
Price	$17,000	$20,000
Fuel Cost	$12 per 100 miles	$4 per 100 miles
Driving Range	400 miles	300 miles
Slow Charging Options		10 min walk from home
		3 min walk from workplace
Fast Charging Time		15 min from empty to full charge
Fast Charging Options		Available within 5 min drive from any place in town
		Available at every 50 miles on highway

Figure 2.1 Screenshot of an example choice task

Table 2.2 shows that respondents intending to buy a used car reported a slightly lower level of education, lower income, and were less likely to be employed than the overall sample. In comparison to the national population, our sample contained a higher proportion of employed people and people with higher education levels. A household income level of $25,000-$74,999 might be overrepresented in our sample. Garage orphans (respondents who answered they only had on-street home parking space or had no accessible electricity outlet for home charging) composed 78 percent of all respondents, while this proportion was even higher among used car buyers (82 percent).

Table 2.2 Background characteristics of the 983 respondents

Variable	Value	Used Car Buyers	All Respondents	National Population
Time Zone	Eastern	46.7%	47.8%	47.6%
	Central	28.9%	28.8%	29.0%
	Mountain	5.4%	6.0%	6.3%
	Pacific	18.8%	17.4%	17.1%
	Total count	**533**	**983**	
Gender	Female	50.7%	49.6%	49.2%
	Male	49.3%	50.4%	50.8%
Education level	Less than bachelor's degree	49.9%	45.9%	69.1%
	Bachelor's degree and higher	50.1%	54.1%	30.9%
Employment Status	Employed	82.0%	84.7%	58.9%
	Not employed	8.8%	6.3%	4.3%
	Other	9.2%	9.0%	36.8%
Household income level	Under $25,000	17.3%	12.6%	21.3%
	$25,000-$49,999	35.1%	31.1%	22.5%
	$50,000-$74,999	23.8%	25.6%	17.7%
	$75,000-$99,999	11.1%	13.8%	12.3%
	$100,000-$149,999	9.3%	12.2%	14.1%
	$150,000 and up	3.5%	4.5%	12.1%
Vehicle ownership	1	56.7%	53.6%	45.8%
	2	32.5%	36.3%	27.2%
	3	8.4%	8.2%	6.3%
	4 or more	2.4%	1.8%	2.2%
Age		Min: 19; Mean: 40.1; Median: 37; Max: 75	Min: 19; Mean: 40.3; Median: 37; Max: 76	Median:38
Used car owner	Yes	87.6%	64.9%	
	No	12.4%	35.1%	
Garage orphan	Yes	82.2%	77.5%	
	No	15.6%	19.4%	
	Other	2.2%	3.0%	
EV owner	Yes	3.8%	7.3%	
	No	96.2%	92.7%	
Monthly long-distance trip	0	33.6%	28.9%	
	1	27.0%	26.7%	
	2	19.5%	23.6%	
	3	8.1%	8.6%	
	4 or more	11.8%	12.2%	

CHAPTER 3. Results

To identify how preferences for EVs differed between new car and used car buyers, we estimated separate choice models for used car buyers and new car buyers. The outcome variable in this study was the stated choice between a gasoline car and an electric car. Therefore, binomial logit models and latent class logit models were employed in this study, with the gasoline car set as the reference alternative. Table 3.1 shows the estimation results of the binomial models for new and used car buyers. The two models included the same set of variables except for home-related slow charging availability. To examine whether the effects of slow charging would be affected by fast charging availability and vice versa, interactions between slow and fast charging were also added to the models.

Table 3.1 Binomial logit choice model results for new EV buyers and used EV buyers (Choice = 1 for EV, 0 for conventional vehicle).

Variables	New EV Buyer Model		Used EV Buyer Model	
	Estimate	Std. Error	Estimate	Std. Error
Constant	0.6978	0.5568	1.2396	0.4664**
Vehicle-related variables				
Price Difference[1] (in $1,000)	-0.0877	0.0114**	-0.1176	0.0165**
Driving range of EV (mile)	0.0039	0.0004**	0.0035	0.0003**
Charging infrastructure variables				
Charging is available at home: 1; Else: 0	0.6529	0.2270**	-	-
Walking distance from home to nearest slow charging (min)	-	-	-0.0603	0.0125**
Walking distance from work to nearest slow charging (min)	-0.0422	0.0133**	-0.0263	0.0110*
Fast charging time (min)	-0.0006	0.0020	-0.0048	0.0018**
Fast charging in town ≤ 15 min drive: 1; Else: 0	0.6979	0.1375**	0.3545	0.1426*
Number of fast charging stations per 100 miles of highway	0.0476	0.0380	0.0220	0.0338
Individual characteristic variable				
Age	-0.0877	0.0246**	-0.0827	0.0206**
Age^2	0.0009	0.0003**	0.0007	0.0002**
Male	0.2740	0.0843**	0.2215	0.0749**
Person has an EV: 1; Else: 0	0.7091	0.1454**	0.4833	0.2027*
Interactions				
Charging is available at home: 1; Else: 0 & Fast charging in town ≤ 15 min drive: 1; Else: 0	-0.3430	0.2696	-	-
Walking distance from home to nearest slow charging (min) & Fast charging in town ≤ 15 min drive: 1; Else: 0	-	-	0.0286	0.0143*
Walking distance from work to nearest slow charging (min) & Fast charging in town ≤ 15 min drive: 1; Else: 0	0.0307	0.0152*	0.0097	0.0129
Number of Observations	2,700		3,198	
Log-likelihood	-1660.83		-2056.54	
AIC	3349.7		4141.1	
Adjusted McFadden Pseudo R-squared	0.111		0.072	

1 Purchase price of EV minus purchase price of gasoline car

Note: *: significance at α=0.10. **: significance at α=0.05. ***: significance at α=0.01.

The latent class logit models were estimated by the “poLCA” package in RStudio. First, the appropriate number of classes was identified by comparing Akaike information criterion (AIC), consistent AIC (CAIC), and Bayesian information criterion (BIC) for models with different numbers of classes. Table 3.2 indicates that although the AIC and CAIC decreased as the number of classes increased, the BIC significantly increased from the three-class model to the four- and five-class models. We made the choice of the optimal number of classes on the basis of the BIC because of the BIC’s greater emphasis on model parsimony, and the easier interpretability this provides. Therefore, we selected the three-class models.

Table 3.2 Information criteria for various number of classes

Model	Number of Classes	Log-Likelihood	AIC	CAIC	BIC
New EV Buyers	2	-1405.9	2849.9	2850.1	2962.0
New EV Buyers	3	-1337.9	2735.8	2736.5	2912.8
New EV Buyers	4	-1317.2	2716.3	2717.6	2958.2
New EV Buyers	5	-1300.8	2705.6	2707.7	3012.4
Used EV Buyers	2	-1640.4	3318.7	3319.0	3434.0
Used EV Buyers	3	-1592.5	3245.0	3245.6	3427.1
Used EV Buyers	4	-1549.1	3180.1	3181.2	3429.0
Used EV Buyers	5	-1527.0	3157.9	3159.7	3473.6

Table 3.3 presents the estimation results of the three-class models for the new and used car buyers. The utility of class 3 was normalized as the reference level for both new and used EV buyers’ models, so the estimates for these three variables were zero. Furthermore, the two models included the same set of variables and the estimates showed high degrees of variation in tastes across the three classes. At first, all the demographic variables were included in the class allocation model. However, many were dropped because of multi-collinearity, and finally age and gender were retained in the class allocation models.

Table 3.3 Latent class choice model results for new EV buyers and used EV buyers

Variables	New EV Buyer Model						Used EV Buyer model					
	Class 1		Class 2		Class 3		Class 1		Class 2		Class 3	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
Result for Three-Class Model												
Constant	-3.005***	0.000	1.462***	0.004	-4.096***	0.000	-2.230***	0.000	-4.494***	0.000	2.002***	0.000
Vehicle related variables												
Price Difference1 (in $1,000)	-0.163***	0.000	-0.110**	0.032	-0.258***	0.000	-0.282***	0.000	-0.054	0.522	-0.259***	0.000
Driving range of EV (mile)	0.009***	0.000	0.004**	0.030	0.003	0.190	0.008***	0.000	0.006***	0.002	0.006***	0.000
Charging infrastructure variables												
Walking distance from home to nearest slow charging (min)	-0.034***	0.005	-0.020	0.353	-0.007	0.825	-0.049***	0.000	-0.432*	0.089	-0.089***	0.000
Walking distance from work to nearest slow charging (min)	-0.036***	0.004	-0.046**	0.041	-0.010	0.757	-0.022*	0.054	-0.043	0.430	-0.053***	0.004
Fast charging in town ≤ 15 min drive: 1; Else: 0	1.891***	0.000	1.021***	0.004	0.549	0.301	0.911***	0.000	1.213**	0.048	0.726**	0.014
Number of fast charging stations per 100 miles of highway	0.062	0.390	0.010	0.888	0.317*	0.098	0.014	0.470	0.317*	0.102	0.044	0.932
Fast charging time (min)	-0.003	0.561	-0.001	0.192	-0.003**	0.024	-0.006*	0.085	0.0003	0.967	-0.016**	0.016
Class Allocation Model												
Constant	1.043***	0.000	0.655**	0.034	0.000	fixed	0.197	0.372	-0.469*	0.053	0.000	fixed
Age of respondent ≥ 40	-0.623**	0.040	-0.848***	0.006	0.000	fixed	0.198	0.439	0.951***	0.000	0.000	fixed
Male respondent: 1; Else: 0	0.160	0.592	0.553*	0.066	0.000	fixed	-0.191	0.437	-0.453*	0.075	0.000	fixed
Membership Probability	0.451		0.346		0.203		0.401		0.261		0.338	
N		2700					3198					
AIC		2735.8					3245.0					
LL		-1337.9					-1592.5					
Adjusted McFadden Pseudo R-squared		0.27					0.27					

1 Purchase price of EV minus purchase price of gasoline car; *: significance at α=0.10. **: significance at α=0.05. ***: significance at α=0.01.

According to the results, the latent class model showed a better fit relative to the binomial logit model, as well as the fact that the latent class model was able to capture the heterogeneity of the respondents. Therefore, here we discuss the results of the latent class model as the final model for further analysis.

3.1. New EV Buyers' Model

The results in table 3.3 indicate three classes of new EV buyers. Class 1 was the largest class, with about 45 percent of the respondents. Among EV-related attributes, the utility of a new EV for respondents in class 1 was mainly influenced by the range and price difference versus an equivalent gasoline car. Also, respondents in class 1 weighed the range of an EV more than respondents in class 2 and class 3. Among charging infrastructure attributes, they were significantly affected by walking distance from home to the nearest slow charging station, walking distance from work to the nearest slow charging station, and whether an in-town fast charging station was available within a 15-minute drive. As can be seen, class 1 respondents considered in-town fast charging more than other classes. According to the class allocation model, respondents in class 1 were more likely to be younger than 40 years old.

Class 2 represented about 35 percent of the respondents. Among EV-related attributes, class 2 respondents considered price difference and EV range as significantly important factors for buying a new EV. From the charging infrastructure perspective, class 2 respondents mainly responded to away-from-home charging opportunities, including work and in-town fast charging. Based on the class allocation model, respondents in class 2 tended to be younger than 40 years old and male.

Class 3 was the smallest class, with about 20 percent of the respondents. In comparison to class 1 and class 2, class 3 respondents appeared to be the most affected by price difference.

Aside from price, class 3 respondents were also sensitive to fast charging time and the spacing of fast charging stations along the highway.

3.2. Used EV Buyers' Model

The results in table 3.3 indicate three classes of used EV buyers. Class 1 was the largest class, with about 40 percent of the respondents. Respondents in this class appeared to consider a larger number of factors in deciding whether to buy a used EV: EV price and range, walking distance from home and work to slow charging stations, fast charging time, and the availability of fast charging stations around town. The only variable that was not a significant predictor of choice in class 1 was number of fast charging stations per 100 miles of highway. Respondents in class 1 were less likely to be male and more likely to be over 40.

Class 2 was the smallest class, comprising 26 percent of the respondents. Among this group, price was not a significant predictor of choice, but EV range was. From the infrastructure perspective, class 2 respondents were sensitive to home charging access, in-town fast charging, and highway fast charging accessibility. Notably, class 2 was the only class for which number of fast charging stations per 100 miles of highway was significant. Respondents in class 2 tended to be older than 40 years old and female.

Class 3 represented about 34 percent of the used car buyers, and this group responded to the same factors as class 1 respondents. While they were similarly sensitive to price and range, class 3 respondents were more sensitive to walking distance from home and work to charging stations, and to fast charging time. They were less sensitive to the presence of fast charging stations in town, though this factor still influenced their choice.

CHAPTER 4. Sensitivity Analysis

After the choice model had been built, a sensitivity analysis was conducted to examine how the vehicle choices of respondents would vary with changes in different predictor variables. This section describes an examination and comparison of the effects of varying different attributes—including characteristics of EVs and charging infrastructures, as well as the trade-offs between those characteristics—on the probability of buying new and used EVs rather than buying new and used gasoline cars in several scenarios. Note that whenever in the following scenarios one or two of the predictors were varied, other predictors were assigned the values indicated in table 4.1. Probabilities were calculated by averaging over all respondents in our sample probabilities predicted by the latent class choice models shown in table 3.3.

The probabilities estimated by using all the variables with the values in this table were 47.0 percent probability of choosing an EV for used car buyers and 51.2 percent for new car buyers. These represented a baseline or reference point for the scenarios that follow.

Table 4.1. The value assigned to other variables when one/two of the variables were varied

Predictor	**Value**
Fast charging in town ≤ 15 min drive: 1; Else: 0	0
Number of fast charging stations per 100 miles of highway	1
Fast charging time	30 min
EV Range	200 miles
Price difference (Purchase price of EV minus purchase price of gasoline car) in $1000	$0
Walking distance from home to nearest slow charging (min)	0 (at-home charging)
Walking distance from workplace to nearest slow charging (min)	0 (at-workplace charging)

4.1. Characteristics of Charging Infrastructures

For one set of scenarios, the impacts of slow and fast charging infrastructure characteristics on the probability of buying an EV were examined.

4.1.1. Fast Charging Facilities

Using the model built in this study, the impacts of fast charging station availability (including in-town and highway charging stations) on the probability of buying a used EV rather than a used gas car and a new EV rather than a new gas car were explored separately.

Figure 4.1 presents the changes in the probability of buying a new EV and a used EV if an in-town DC fast charging station with different charging times is accessible by driving no more than 15 minutes. The solid lines show how the average choice probabilities varied with fast charging time at in-town charging stations. The dashed lines show the reference-level choice probabilities, with no in-town fast charging available. Several features of figure 4.1 are notable. Both used and new car buyers showed sensitivity to in-town fast charging. Used car buyers were somewhat more sensitive to charging time than were new car buyers. However, both groups were influenced much more by the simple presence of in-town fast charging than they were by the actual charging time (at least over the range of charging times that was considered in this work).

The impacts of a highway fast charging station available within every 100 miles of highway with different charging times on the probability of buying an EV are displayed in figure 4.2. In contrast to in-town fast charging, the effects of charging time at highway fast charging stations were greater on new car buyers than on used car buyers, but both were less sensitive to highway charging than they were to in-town fast charging times.

4.1.2. Trade-off between Fast Charging Facilities

By comparing figure 4.1 with figure 4.2 for used car buyers it was possible to estimate the number of fast charging stations per 100 miles on the highway that would provide the same utility as having fast charging available within a 15-minute drive in town. The results are summarized in table 4.2 for different fast charging times. Because a highway fast charging station was shown to only slightly affect new car buyers, they are excluded from table 4.2.

Table 4.2 The spacing of highway fast charging stations that provides equivalent utility to having in-town fast charging available within 15 minutes from anywhere in town. (For used car buyers.)

Fast charging time	Equivalent number of highway fast charging stations in 100 miles	Spacing of highway fast charging stations (miles)
5	3.8	26.3
10	4.5	22.2
15	5.5	18.2
20	7.5	13.3
25	12.6	7.9

4.1.3. Slow Charging Facilities

For this scenario, the effects of decreased walking time to the nearest slow charging facility on EV choice probabilities was assessed both for home and workplace charging opportunities.

As shown in figure 4.3, decreasing the walking time from home to the nearest slow charging facility available was found to have a stronger effect on used car buyers than on new car buyers. However, the decreased walking time from workplace to the nearest slow charger available, as shown in figure 4.4, had a similar effect on both used and new car buyers to choose an EV over a gas car.

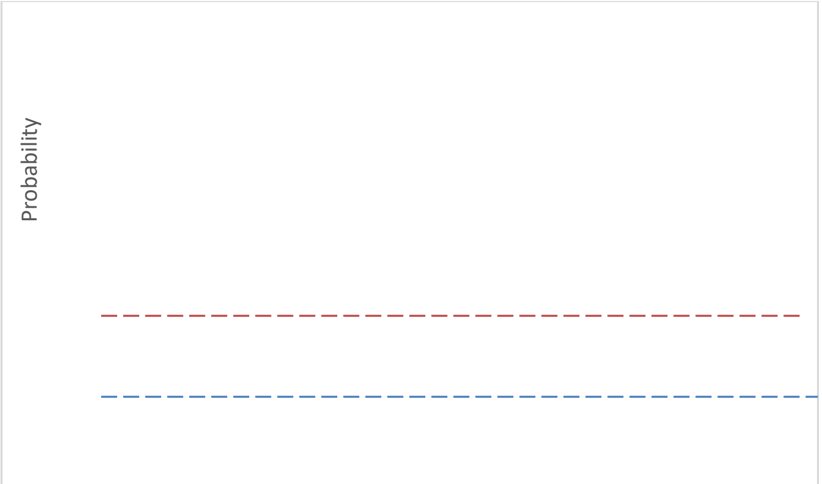

Figure 4.1 Impacts of an in-town fast charging station with different charging times on the probability of buying an EV

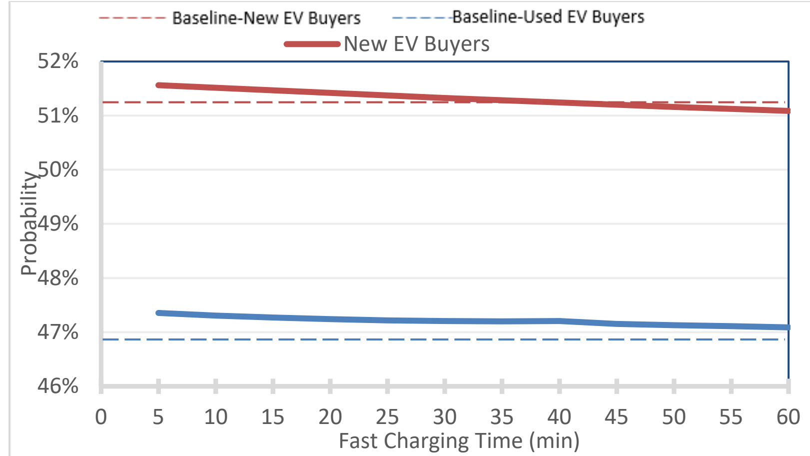

Figure 4.1 Impacts of a highway fast charging station in 100 miles with different charging times on the probability of buying an EV

Figure 4.3 Impacts of different walking times from home to the nearest slow charging facility on the probability of buying an EV

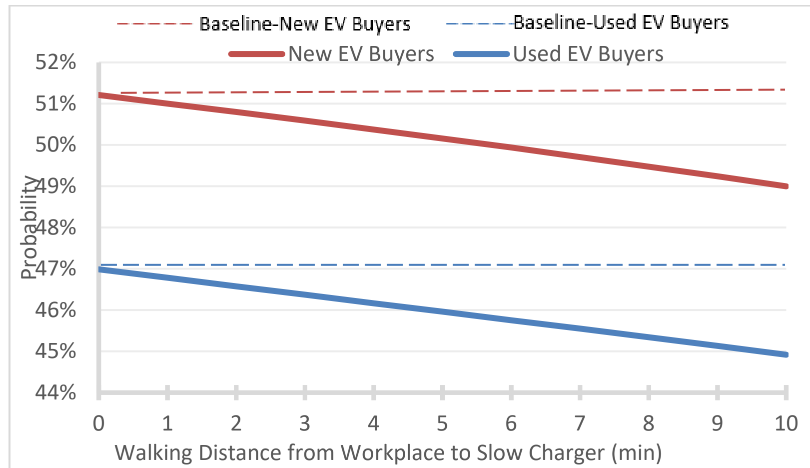

Figure 4.4 Impacts of different walking times from workplace to the nearest slow charging facility on the probability of buying an EV

4.2. Characteristics of Electric Vehicles

The two main characteristics of an electric vehicle found to be significant in the final model were (1) the price difference between an EV and an equivalent gasoline car, and (2) the range of the EV. This section describes and examination of the impacts of each EV characteristic, separately and as a trade-off with others.

4.2.1. Electric Vehicle Price and Range

The effects of varying price difference and EV range on the probability of buying an EV, for both used and new car buyers, are displayed in figures 4.5 and 4.6, respectively. As can be seen, used EV buyers were found to be slightly more sensitive to price difference than new EV buyers.

In addition, figure 4.6 indicates that increased EV range has virtually the same effect on the probability of buying an EV rather than a gas car for both used and new car buyers.

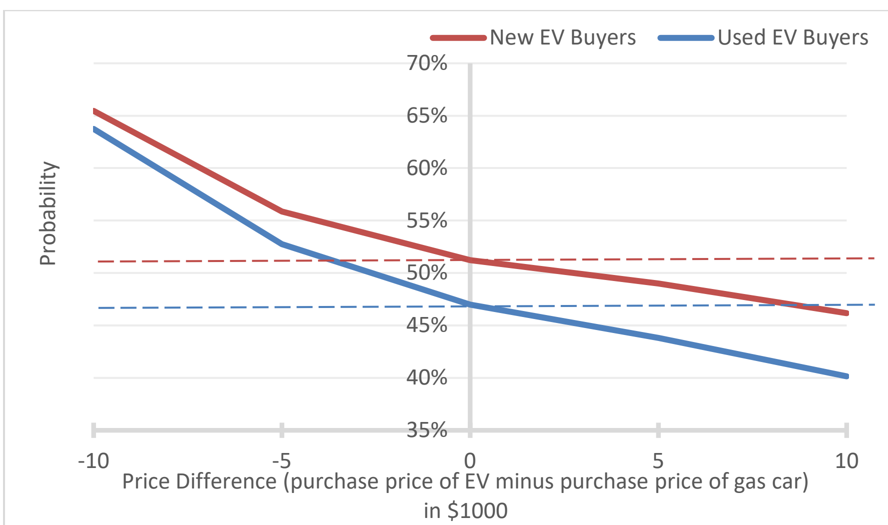

Figure 4.5 Impacts of various price differences on the probability of buying an EV

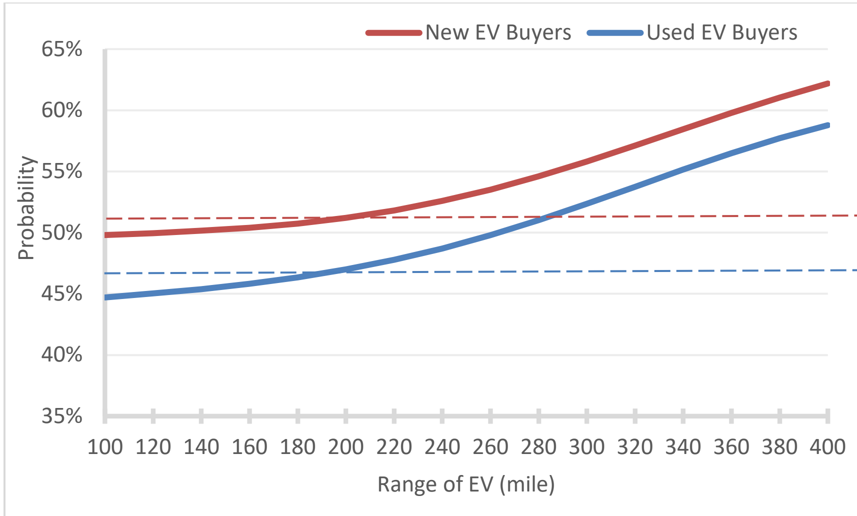

Figure 4.6 Impacts of EV range on the probability of buying an EV

4.3. <u>Trade-offs between Characteristics of Electric Vehicles and Charging Infrastructure</u>

As mentioned, one of the important factors that could encourage a potential buyer to choose an EV, either new or used, over a gasoline car is home charging availability and/or proximity to a slow charging facility for those who are not able to charge their car at home. For this scenario, we calculated the change in price needed to maintain the utility constant as walking time from home to the charging location increases by one minute. Results showed that if the purchase price difference decreased about $176 for new car buyers and $194 for used car buyers with every 1 minute increase in the walking time from home to the nearest slow charging facility, the utility of buying an EV would not change. This finding suggests that for a potential buyer who is not able to charge at home, a minimum decrease in EV purchase price of $176 for new car buyers and $194 for used car buyers might encourage them to consider buying an EV rather than a gasoline car.

CHAPTER 5. Conclusions

This study analyzed the results from an online stated preference choice experiment involving private car owners in the U.S. that aimed to examine and compare the effects of EV and charging infrastructure characteristics on the preferences for EVs of new and used car buyers. Most previous studies have focused only on new car markets, while the differences between new and used car buyers have been ignored. In this regard, two separate latent class models with three classes were built for used and new car buyers. In addition, a detailed analysis of EV and charging infrastructure characteristics was conducted to support the roll-out of EVs. Our results showed that while new and used car buyers share similar patterns in preferences for EVs, they have different sensitivities to price difference between EVs and gasoline cars, and to the characteristics of charging infrastructure, including fast charging time, accessibility to in-town fast charging, highway fast charging, and home charging facilities.

The latent class model suggested that different groups of car buyers respond to different types of EV charging infrastructure. The largest groups were found to respond to having fast charging stations available in town, and to having shorter walking access from charging stations to home and work. Smaller groups of both used and new car buyers were found to be more sensitive to fast charging time and to the spacing of fast charging stations along the highway. Results from the sensitivity analysis showed that used EV buyers are slightly more sensitive to price difference than new EV buyers, while increased EV range had virtually the same effect on the probability of buying an EV rather than a gas car for both used and new car buyers.

The results of this work can be applied to quantify the tradeoffs between different types of investments in charging infrastructure. For example, the models can be used to determine what factors have the greatest effects on purchase choices: neighborhood slow charging near homes and workplaces, in-town fast charging stations, highway corridor fast charging, and conventional fast charging versus extreme fast charging.

Because the study was based on a stated preference choice experiment, to reduce respondents' choice burden, among many charging infrastructure characteristics only a limited number of attributes were included in the choice tasks. On the basis of this limitation and the findings of this study, we recommend several future research opportunities regarding the impacts of charging infrastructure on consumer preferences for electric vehicles. First, in addition to proximity, factors to explore may include how slow charging time and parking safety affect car buyers' preferences for slow charging at public charging stations. Second, this study did not distinguish between the charging costs of slow and fast charging. Investigating the effects of charging costs and how they interact with charging type and location would add to the design of a more effective charging network. Lastly, local context is very important for any infrastructure investment. Future research on EV charging infrastructure could build on this nationwide study to conduct local-specific analysis in detail.

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