©Copyright 2018

Parasto Jabbari

The role of market scale in electric vehicle adoption: consumer and infrastructure perspectives

Parasto Jabbari

A thesis
submitted in partial fulfillment of the
requirements for the degree of

Master of Science in Civil and Environmental Engineering

University of Washington

2018

Reading Committee:

Don MacKenzie, Chair
Jeff Ban
William Chernicoff

Program Authorized to Offer Degree:

Department of Civil and Environmental Engineering

University of Washington

Abstract

The role of market scale in electric vehicle adoption: consumer and infrastructure perspectives

Parasto Jabbari

Chair of the Supervisory Committee:

Don MacKenzie

Department of Civil and Environmental Engineering

This thesis seeks to improve understanding of the role of market scale in electric vehicle (EV) adoption, by exploring consumer and infrastructure perspectives. First, we use new vehicle post-purchase consumer satisfaction survey to explore the reasons for low EV adoption. We investigate consumers' level of satisfaction and reasons for rejecting a vehicle using matching method and statistical tests. Results show that plug-in electric vehicle (PEV) purchasers and considerers are less satisfied with their overall purchase experience compared to internal combustion engine (ICE) vehicle purchasers and considerers, but PEV considerers are less likely than ICE considerers to cite the dealer's attitude as a reason for rejection. Price and value are the most cited reasons and were similarly important for both groups. Reasons related to model availability and vehicle attributes are more often a concern for PEV considerers than ICE considerers. These results suggest that even with existing incentives, the limitations of the current technology, mainly price and range, and variety of available vehicles, are the most important challenges for EV adoption. However, market growth has the potential to resolve most of these barriers. Since range anxiety is still a major barrier for EV adoption, even for those who already are considering purchasing EVs, we take another step to understand impact of market scale on charging infrastructure reliability, utilization and cost effectiveness. We build a queue model informed by the characteristics (e.g. charging rates, battery size, range) of current battery electric vehicles (BEVs) and available DC fast chargers. We use the model to determine how we can expect costs, utilization and availability of chargers to change with respect to each other and find out what the costs are for maintaining satisfactory availability for users. The model shows that for a charging station with few chargers, it is difficult to achieve cost-effective levels of utilization while maintaining reliable access for arriving vehicles. Large numbers of chargers per station make it possible to maintain a high reliability of access for users and a high utilization rate. Also, as the number of EVs on the road increases, the business case for DC fast chargers becomes more attractive.

Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction and background

1.1 Why promoting electric vehicles?

It has been more than 100 years since the electric vehicle (EV) was first invented [1]. As personal cars were finding their place in people's lives around that time, the popularity of electric cars increased mainly because compared to other available options for personal cars, gasoline and steam vehicles, electric cars had less noise and smell and they did not need as much manual work to operate [1]. However, as gasoline-powered vehicles' technology improved, and their price dropped, electric cars could no longer compete. Since the invention of electric vehicles, there have been many rises and falls in their popularity, mostly as the result of changes in the oil market [1]. It was only with the rise of environmental concerns in 1990s, that the interest in electric vehicles was revived. Since then EVs are considered as part of the solution to alleviate environmental issues and oil dependencies.

Fossil fuels are a non-renewable source of energy and have formed over millions of years. That means they do not replenish in a short time [2, 3]. Based on U.S Energy Information Administration [4], in 2016, petroleum products comprised 92% of the total energy used in transportation sector and light-duty vehicles were responsible for 90% of gasoline consumption in the nation. In their study of sustainability in urban areas, Van Wee et al. [5], have explained that electric vehicles can bring considerable benefits to energy consumption. The amount of benefits depends on the life-cycle of the vehicle and their energy consumption from "well-to-wheel". As the nation moves toward using renewable energy sources such as wind, solar, etc., to produce electricity, electric vehicle's energy consumption will rely less and less on fossil fuels.

Another important characteristic of EVs is that all-electric vehicles have zero direct or tailpipe emissions. This means since they use electricity to run, they do not emit the pollutants that internal combustion engine (ICE) vehicles do. The health risks of pollutants are serious. Poor air quality can cause respiratory ailments and increase the risk of cardiovascular diseases, it can also adversely affect pregnancy, and cause death [6]. Replacing ICE vehicles with EVs can directly improve air quality of urban areas. The total amount of emissions produced by EVs in their life cycle depends on source of electrical power and it varies based on the geographical location. In general, EVs' life cycle emission is not as much as ICE vehicles [7, 8, 9] and, as mentioned above, shifting from fossil fuels to renewable energy sources will result in reduction of total emission produced.

Beside the fact that EVs contribute to urban air quality and health of individuals, they play an important role to control climate change. Some of the pollutants from combustion, such as CO_2, contribute to warming the Earth's atmosphere [10]. Climate change not only influences the air quality (by increasing ground-level Ozone), but also causes shrinkage of glaciers, rise of sea level, more intensive heat waves and changes in precipitation patterns [11], that ultimately results in substantial changes in ecosystems [12].

The social impacts of the EVs were described in above paragraphs. However, on private and individual levels, EV's have the potentials to benefits users that make them appealing for users. Some of the most important ones is that the cost of operating an EV is usually lower than the cost of operating conventional vehicles. The amount of benefits from driving EV can vary and depend on gas and electricity price at different geographical locations. The average price of gasoline in U.S. for first two months of 2018 is $2.56 per gallon [13] and $1.18 for electric eGallon (cost of charging an EV compare to similar conventional vehicle to drive same distance) [14], that result in considerable savings.

EVs have the potential to be safer than comparable conventional vehicles. A study of EVs performance in crashes [15] shows that EVs are "more crashworthy than their conventionally powered counterparts" for the variety of tested vehicles and scenarios. They have less harm for passengers in frontal collisions, since EVs do not have engines and their electric motor is usually in the back. National Highway Traffic Safety Administration (NHTSA) ratings for high selling EVs (Tesla Model X, Tesla Model S, Toyota Prius, Chevrolet Volt, etc. [16]) shows that they are competitive with conventional vehicles [17]. On the other hand, there are still uncertainties on how safe lithium-ion batteries are [18] and manufacturers are working on improving their safety.

The EV advantages counted above, have led government and policy makers to see EVs as a solution for many environmental and energy concerns that our world is dealing with. To promote EVs among users, policy makers have come up with several different strategies that include incentives, regulations, mandates, etc. Federal and state tax exemptions is one of the incentives provided for the purchasers to lower up-front costs of EVs. The amount of federal tax credit is $2,500 to $7,500 for each EV and the exact amount depends on the size of the vehicle and battery capacity [19]. States have their own specific incentives. For example, in Washington State, eligible EVs with base model price of $42,000 or less, will receive a tax exemption applied to up to $32,000 of the selling price of the vehicle. The range of incentives for other states can vary from access to High Occupancy Vehicle (HOV) and High Occupancy Toll lanes to rebates on EV purchase or lease [19]. Zero Emission Vehicle (ZEV) program, Corporate Average Fuel Economy (CAFE) program, and EPA's light duty vehicle GHG emissions program are examples for regulations and mandates. ZEV program requires manufacturers that certain percentage of their sales be zero-emission vehicles [20]; while CAFE and EPA's light-duty vehicle GHG emission program requires them that vehicles produced by 2025 meet an estimated combined average fuel economy of 48.7 to 49.7 miles per gallon or higher. Based on these programs manufacturers can earn credits for alternative fuel vehicles [21].

1.2 Major barriers of EV adoption

Even though there are many advantages to EVs, they are making EVs attractive in general terms and they do not address specific concerns of consumers. As a result, their adoption pace is slower than what was hoped for. Researchers, policy makers, and industry point to many barriers on the way of widespread adoption of plug-in electric vehicles, including range anxiety, lack of charging infrastructure, high costs, and others. Numerous studies have tried to understand and address these barriers [22, 23, 24, 25, 26, 27]

Range anxiety is a key disincentive to the adoption of EVs. It is defined as the fear of fully depleting PEV's battery in the middle of the trip, leaving the driver stranded or forced to make a lengthy stop for recharging. This can cause drivers to choose a gasoline vehicle over an electric vehicle, thus preventing EVs from gaining a significant share of the vehicle market [28]. Neubauer and Wood [28] noted that "increased range anxiety was regularly shown to decrease vehicle utility" and concluded that additional access to recharging infrastructure would reduce the impact of range anxiety and investing in refueling infrastructure has the potential to improve vehicle utility considerably. Thorough reviews of related literature can be found in Hoen & Koetse [29] and Tanaka et al [30].

High price and lower performance of initial models of electric vehicles compared to ICE vehicles made it harder to improve EV sales. In recent years, we have seen noticeable improvements in performance of EVs []. However, for the case of the price it is more complicated. Demand and supply are interdependent. As the demand for EVs increases we can expect the supply increase and as a result production cost of EVs goes down (since fixed costs of production will divide over more units of product) but for adoption and demand to rise, price of EVs need to go down first. This is where incentives and tax breaks play their essential role. The same issue stands for charging infrastructure. The high costs of deployment of these facilities make it difficult to maintain desirable utilization and profitable investment while the adoption is low.

Unfamiliarity with EV technology is another key barrier for EV adoption. As noted by Gould & Golob [25], "instead of embracing new energy technologies, some rely on notions of tradition and familiarity when they make consumer choices." When consumers become familiar with new technology through media and expert opinion, interpersonal communications, or direct experience with vehicle, the investment in such technology feels less risky and consumers are more willing to adopt [25, 26, 32, 33, 34]. The need for this exposure tends to concentrate potential PEV adopters among groups with specific demographics. Acceptance of new technology depends on individuals; and as expected, individuals' characteristics such as gender, age, personality and other can be influential [26]. Several studies recognize these characteristics among PEV adopters. Some studies indicate that being technophiles and having environmental concerns as PEV buyers' notable characteristics [23, 35, 36]. Being highly educated and a previous owner of a hybrid car are others [36]. Even among "technologically minded" individuals, the perceptions of PEVs vary with demographics such as gender, level of education, and age [23].

1.3 Thesis Overview

This thesis seeks to improve understanding of market scale role in EV adoption by investigating consumers behavior toward purchasing EVs and infrastructure utilization tradeoffs with reliability of the facilities. It explores consumer choices and rejection reason to understand the EV market from consumer perspective and uses queuing model simulation, to understand EV market impact on charging infrastructure.

In Chapter two, we use an extensive new vehicle post-purchase consumer satisfaction survey to explore respondents' reasons for rejecting PEVs, and among those who ended up purchasing PEV, we investigate how satisfied they were with their purchasing experience at dealership. Respondents of this survey have passed the familiarity stage and have purchased or considered to purchase PEV. However, they are still early adopters and as mentioned in the previous section, they have unique characteristics. To make sure our analysis is unbiased, we match them with similar ICE purchasers and considerers based on their demographics and geographical location. Then we use the resulting matched dataset to test for differences in satisfaction and reasons for vehicle rejection between ICE and PEV purchasers and considerers. The differences allow you to gain insight into factors that limit EV adoption and may serve as barriers.

Based on the findings of chapter two and what previous research and literature has suggested, in chapter three, we investigate one of the most important barriers of adopting PEVs, lack of charging infrastructure. We explored how providing reliable access to charging infrastructure impacts utilization of the facility and what are the tradeoffs between reliability and utilization. To do so, we use queuing model to simulate charging behavior from arrival to departure from the facility. Then we proposed co-locating multiple DC fast chargers at a single station to maintain high utilization while providing reliable service for customers and we looked into the business model of providing such service and how cost-effective it will be.

In Chapter four, the main findings of two previous chapters are summarized and reviewed. The goal of this thesis was to understand the role market scale plays in EV adoption and recognize the reasons that are keeping EV adoption from achieving goals and expected projections. In the final chapter, based on our findings, we highlight areas that have potentials for improvement and policy makers and regulators can pay attention to them.

Chapter 2: Analysis of electric vehicle purchaser satisfaction and rejection reasons

Acknowledgment

This chapter is based on a paper jointly authored with William Chernicoff and Don MacKenzie, published in Transportation Research Record: Journal of the Transportation Research Board, No. 17-04996, pp. 110-119. (c) National Academy of Sciences, Washington, D.C., 2017. Material in this chapter is reproduced with permission of the Transportation Research Board. None of this implies endorsement by TRB of a product, method, practice, or policy.

2.1 Background and Research Question

In the last couple of years there have been a great focus to remove the barriers of PEV adoption that resulted in improvements in battery technology, cost, and charging infrastructure availability [37]. These improvements, and the resulting vehicle design changes is expected to have helped overcome range anxiety and unreliable access to charging facilities. Vehicle cost reduction along with federal and state tax incentives for PEVs, made purchasing more affordable. PEV annual sales has grew from 2011 to 2014 [38] However, in 2015 sales fall short from official goals [39] and a 2016 report by Federal Highway Administration shows that sales did not meet modeled projections [40].

For adoption to grow, awareness must turn into consideration, and consideration into purchase. Therefore, it is worthwhile to study what happens when people are considering purchasing PEVs: Did they ultimately buy a PEV? Were they satisfied with the experience? If they chose not to purchase a PEV, what aspects of the vehicle and purchase experience turned them off? Understanding this consumer decision process is important to broaden the PEV market from innovators to the early adopters who may be more sensitive to these rejection factors [41]. However, there is a lack of systematic research in this area, mainly due to a lack of robust data. One study using data from the J.D. Power 2013 Sales Satisfaction Index investigated customer satisfaction of PEV purchasers. Mixed effects regression is used to adjust for race, gender, income, and selected other covariates, and concluded that PEV purchasers are less satisfied than conventional vehicle purchasers [42]. However, comparing PEV purchasers with ICE purchasers does not provide insights into the choices or purchase experience of those who considered, but did not buy, a PEV.

In this chapter, we address the following questions:

- **Question 1:** Do PEV purchasers report different levels of satisfaction with the dealership purchasing experience than do similar conventional vehicle purchasers?
- **Question 2**: Do consumers who considered a PEV but ultimately purchased another vehicle report different levels of satisfaction with the dealership purchasing experience than do similar consumers who considered an ICE but ultimately purchased another vehicle?
- **Question 3:** Do the reasons cited by consumers who considered a PEV but ultimately purchased another PEV or non-PEV differ from those cited by similar consumers who considered one ICE but ultimately purchased another ICE or non-ICE?
- **Question 4**: What factors leading to rejection of a considered vehicle are significantly more common among those who considered a PEV than among those who considered a conventional vehicle?

We note here the important difference between statistical and practical significance, and where appropriate comment on the practical significance of the results.

The data used for this analysis is MaritzCX data held by Toyota Motor Sales, and used with permission of MaritzCX. The data include 1,007,040 consumer responses to the New Vehicle Consumer Satisfaction Survey for years 2011-2015 to a wide range of questions (78) on vehicle purchase decisions (table 3), satisfaction, and their background information [43]. Table 1 shows the proportion of PEV purchasers and considerers by year. We have complete data on which powertrain each respondent purchased, but only a subset of respondents answered the questions about other vehicles considered.

Table 1. Counts of Purchasers and Considerers by Year and Powertrain

			Answered questions about vehicles considered					
	Total purchasers (implicit consideration)		Total considerers		Considered and purchased same powertrain		Considered but rejected the powertrain	
	PEV	ICE	PEV	ICE	PEV	ICE	PEV	ICE
2011	473	170,301	113	90,285	1	80,368	112	9,917
2012	2,192	149,684	644	79,352	394	68,629	250	10,723
2013	4,085	141,594	1,157	79,115	807	63,109	350	16,006
2014	3,980	126,219	1,183	66,889	819	54,983	364	11,906
2015	5,125	191,582	1,481	84,321	1,060	71,478	421	12,843

The numbers related to PEVs vary somewhat in the earlier years before stabilizing somewhat in the 2013-2015 period. Overall, about 2.8% of respondents chose a PEV, and the consider-then-reject rate for PEV powertrains in was 30% in 2013-15.

2.2 Methodology

The goal of our analysis is to identify differences in purchasing experience and reasons for choosing or rejecting vehicles due to the type of vehicle (PEV or ICE) purchased. A key challenge is selection bias: the customers who choose different powertrains may have different underlying values, preferences, and expectations, which themselves influence the customers' satisfaction and confound differences due to the actual purchasing experience. We therefore want to control for differences in key observable characteristics such as income, location, and education level, which are likely to be correlated with the underlying preferences and expectations. Two general approaches to controlling for confounders are adjustment (regression) and balancing (matching). We use the latter approach in this paper.

The first step of our analysis is to match each member of the first group (e.g. PEV purchasers) with a similar individual from the second group (e.g. ICE purchasers) in terms of age, gender, income category, education level, and state of residence [44, 45]. As discussed in the introduction, existing purchasers of PEVs appear to fall into several specific demographic archetypes that are meaningfully differentiated from the general purchasing public. For example, different groups of people have different expectations of their experience and what they are looking for. In addition, prior work shows that "psychographic and behavioral characteristics" can significantly influence vehicle choice [46]. The matched groups are then compared to estimate the differences attributable to the vehicle choice.

Matching (otherwise known as selection on observables) is a less model-dependent approach than regression-based techniques. Whereas regression controls for differences in covariates through adjustment (adding together estimated effects of covariates on the outcome of interest), matching controls for differences in covariates through balancing (comparing members of one group with similar members of another group, so that on average the covariate distributions in both groups are approximately the same). In contrast to regression-based methods, the validity of this matching approach is not contingent upon assuming the correct model specification and is more robust to the myriad nonlinearities and interactions that may link the covariates and outcome variables [47]. Matching has been widely applied to problems such as measuring changes in vehicle technology [48, 49], the effects of smoking [50], the effects of carsharing [51] and residential location choice [52] on travel demand, and the economic impacts of new roads [53], among many other problems.

Our data set contained a large number of covariates on which to match respondents. To obtain valid estimates of the effect that vehicle choice has on subsequent decisions and satisfaction, respondents should be matched on covariates that are determined before the vehicle choice occurs [50]. We exactly matched individuals with the same genders, who are in the same education and income categories, in the same state, whose age difference is not more than 3 years. There might be other factors, such as number of vehicles in the household, affecting vehicle type choice [46]. However, most of these factors have some sort of correlation with the factors we observed. Except for California, other states, and specific geographic location did not have enough data to extend the analysis to include other covariates. Due to the large number of respondents, we had no problems finding matches for most of the questions; we were able to find at least one match from the “control group” for our “treated group” individuals. Based on the specific research question, the definition of treated and control group varies throughout this paper. In general, the treated group is the group who purchased or considered purchasing a PEV. Summary statistics of the matching method for each question are in the results section.

For the questions about overall satisfaction with purchasing experience, the dependent variable (level of satisfaction) is ordinal and not normally distributed. Consequently, we cannot use the most common tests such as the t-test, and instead used the Wilcoxon signed rank test for paired data [54]. The Wilcoxon signed rank test is used to test whether the medians for two paired samples are the same or not [54, 55] The null and alternative hypotheses for our questions are:

H_0: The median levels of satisfaction in the two matched groups are equal.
H_1: The median levels of satisfaction in the two matched groups are not equal.

Levels of satisfaction with overall purchase/lease experience at dealership are reported on a Likert type scale with the following values:

1: Very Dissatisfied
2: Somewhat Dissatisfied
3: Satisfied
4: Very Satisfied
5: Completely Satisfied

We used a significance level of $\alpha = 0.05$ to assess statistical significance.

To determine whether the reasons cited by consumers who considered but rejected a PEV differ from those cited by similar consumers who considered but rejected an ICE, the Wilcoxon signed rank test is no longer appropriate since the dependent variable is no longer ordinal. Therefore, we use both chi-squared and McNemar tests.

The Chi-squared test tells us if the probability of selecting a reason is independent of the powertrain chosen and allows us to consider all (matched) observations. However, the downside of chi-squared is that it does not account for the paired structure of our data. Moreover, since it uses all of the control units, our data set is unbalanced in the covariates and self-selection bias may affect the results. To overcome this limitation, we use the McNemar test which is designed for paired data.

The McNemar test is used to test "marginal homogeneity in 2x2 tables" which means that marginal frequencies in the table are equal or not. It is widely used in medical and human behavior research or other areas when the impact of a treatment or before-after differences for a paired sample is targeted [47, 56, 57]. The problem with the McNemar test is that it requires 1 control unit per treatment unit, but because of our large sample size many of our treated units have multiple (up to 63) equally appropriate control units. Our matching algorithm (the matching() function in R) randomly selects one control unit from all eligible matches, but the specific control unit selected can lead to differences in statistical results (i.e. p-values). To address this issue, we ran 150 repetitions of the matching algorithm, conducted the McNemar test on each resulting matched set, and have reported the average p-value from these 150 runs.

A 2x2 McNemar table looks like table 2:

Table 2. McNemar 2X2 Table Sample

ICE considerers / PEV considerers	+	-	Total
+	a	b	a + b
-	c	d	c + d
total	a + c	b + d	a + b + c + d

+ means that the individual chose it as one of the reasons for rejecting the considered vehicle and – means that individual did not choose it as one of the reasons for rejecting the considered vehicle. If both individuals (both PEV considerer and ICE considerer who are matched) in a pair have chosen that reason they would belong to N_{++} category. If they both have not chosen that reason they would belong to N_{--}. If an individual who belongs to the PEV considerers sample has chosen that reason but the individual from ICE considerer has not, the pair would belong to N_{+-} and if an individual who belongs to the ICE considerers group has chosen that reason, but the other individual have not, the pair would belong to N_{-+}. The number of pairs in each category would enter the 2x2 table. "a" is number of pairs N_{++}, "b" is count of pairs in N_{+-} ,"c" is number pairs in $N_{-+,}$ and "d" is number of pairs in N_{--}. N_{-+} and N_{+-} are called discordant cells. The null hypothesis for McNemar test is: the discordant has equal values. This means that the outcome of the test is independent from treatment.

In our analysis the null and alternative hypotheses are:

H_0: Reasons for rejecting a considered vehicle are independent from the powertrain considered
H_1: Reasons for rejecting a considered vehicle are dependent on the powertrain considered.

We repeated this test for all the rejection reasons indicated by consumers. Table 3 shows the available reasons for respondents to choose from. To determine whether the reasons are independent of powertrain or not we used a significance level of $\alpha = 0.05$. However, since we are conducting these tests on multiple reasons, we apply a Bonferroni correction to reduce the risk of false positives. Thus, we judged statistical significance by a p-value of less than 0.05 / 27 = 0.00185 [58]. Analysis for all tests was done in R statistical software package.

Table 3. Reasons for Not Selecting the Most Serious Considered Vehicle Provided by MaritzCX Consumer Survey [43]

Reasons for Not Selecting the Most Considered Vehicle			
1.Manufacturer's Reputation	8.Exterior Styling	15.Cargo Capacity	22.Financing Terms/Rebate
2. Vehicle Size/Trade	9.Engine Performance/Power	16.Riding Comfort	23.Lease Option Not Available
3. Interior Styling	10.Fuel Economy	17.Value for the Money	24. Communication System Not Available (e.g., telematics, OnStar, Tele Aid, etc.)
4. Safety Features	11.Future Trade-in/Resale Value	18.Available Options/Equipment	
5. Overall Quality/Reliability	12.Price/Deal Offered	19.Warranty Coverage	25.Model Not Available at Dealership
6. Attitude of Dealer Personnel	13.Interior Roominess	20.Ease of Handling	26. Environmental Friendliness
7.Seating Capacity	14.Rear Leg Room	21.Country of Manufacturer	27.Other

2.3 Results

2.3.1 Matching Result

Figure 1 to 5 contains the summary statistics of the four chosen characteristics of individuals for unmatched samples of ICE purchasers and PEV purchasers. Figure 1 shows that average age of PEV buyers is around 52.1 and for ICE buyers is 53.6. PEV buyers are slightly younger than ICE buyers.

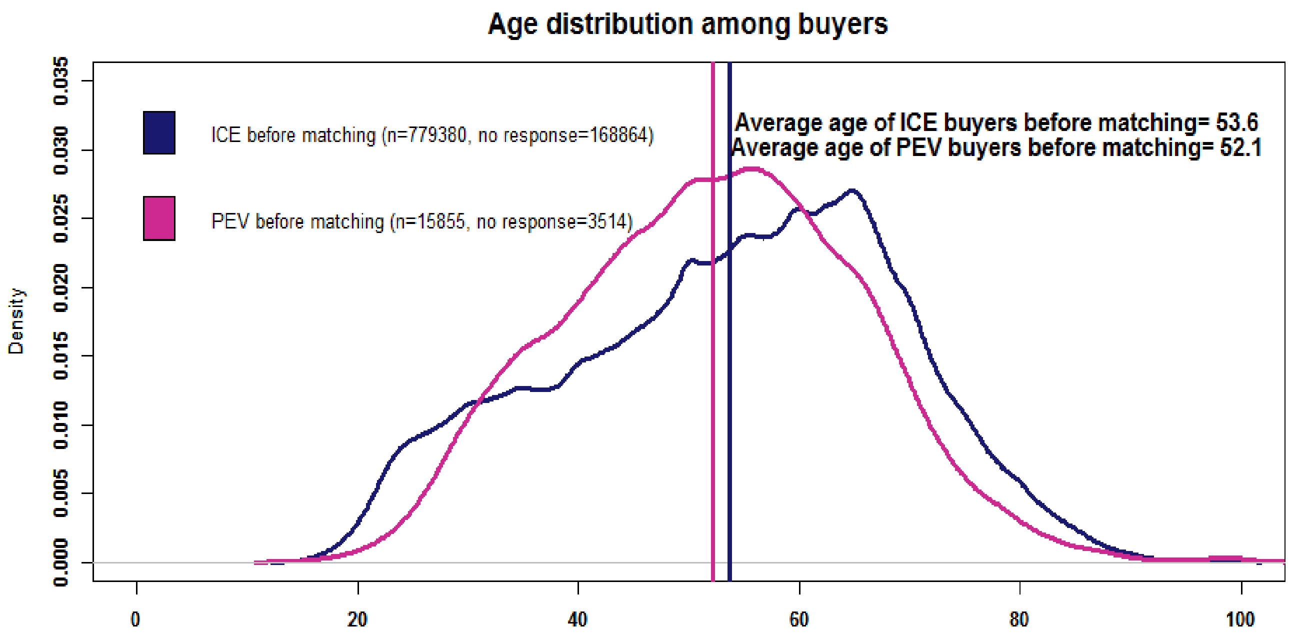

Figure 1. Age distribution of car buyers for two powertrains.

Figure 2 demonstrates income distribution of PEV and ICE buyers. It shows that median income of ICE buyers is in $85,000 to $100,000 bracket but for PEV buyers, the median income is in $125,000 to $150,000 bracket. In our data, PEV buyers are wealthier than ICE buyers.

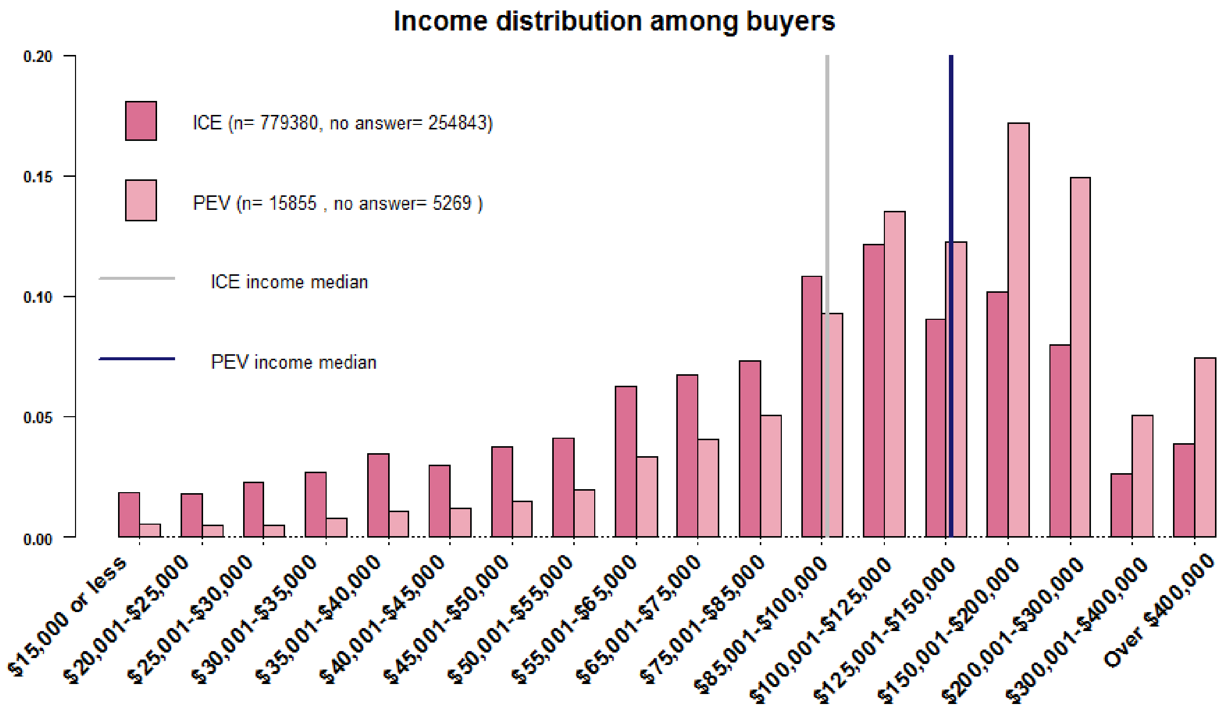

Figure 2. Income distribution of car buyers for two powertrains.

Next, we looked into the education level among vehicle purchasers in our sample. We find out that PEV buyers have higher education compare to ICE buyers (figure 3). This is consistent with what literature suggested about characteristics of PEV buyers ().

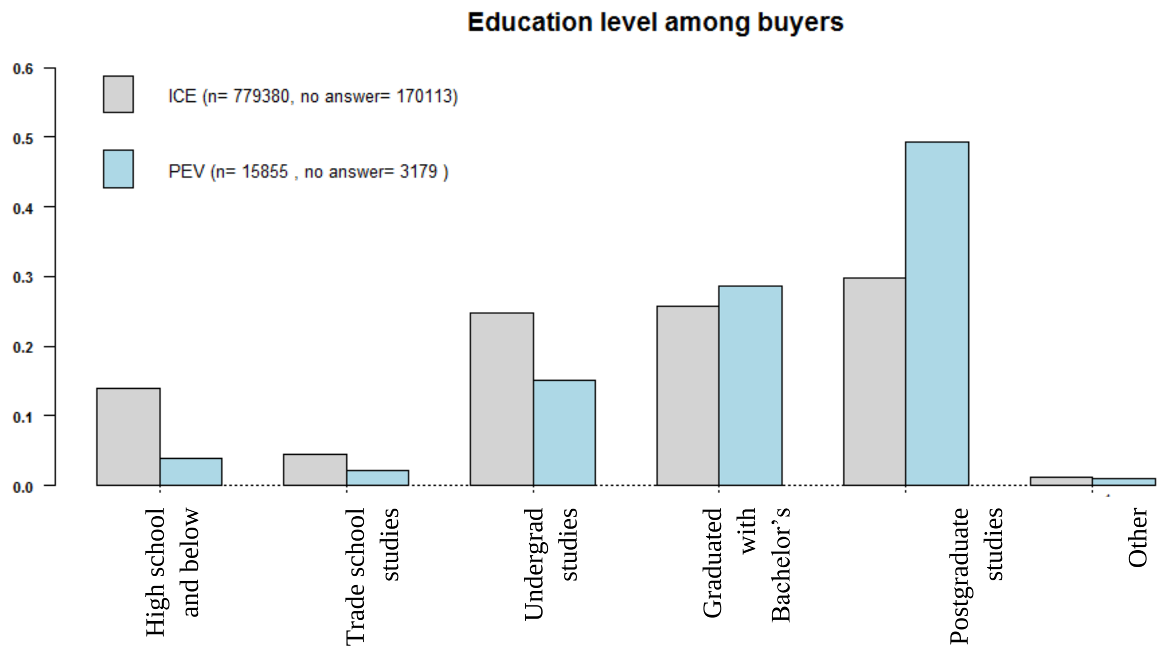

Figure 3. Education level among vehicle buyers for tow powertrains.

We also looked into the residency of buyers in our sample. We find a very different distribution for ICE buyers and PEV buyers (figure 4).

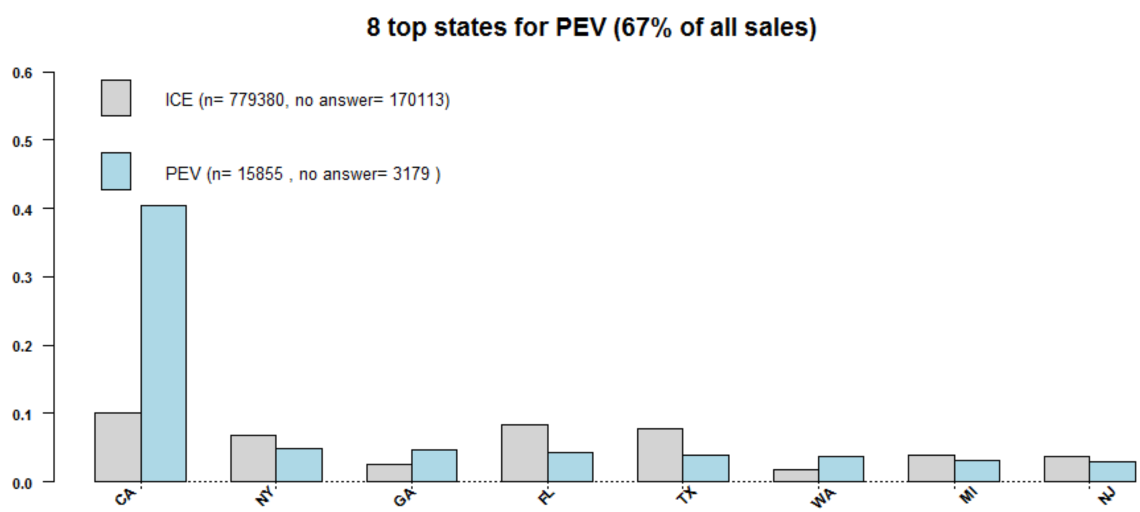

Figure 4. Eight top states in sales for PEVs in our sample.

For gender, before matching, ICE purchasers were 31% females, 48% males and 21% not answered; PEV purchasers were 22% females, 57% males and 21% not answered.

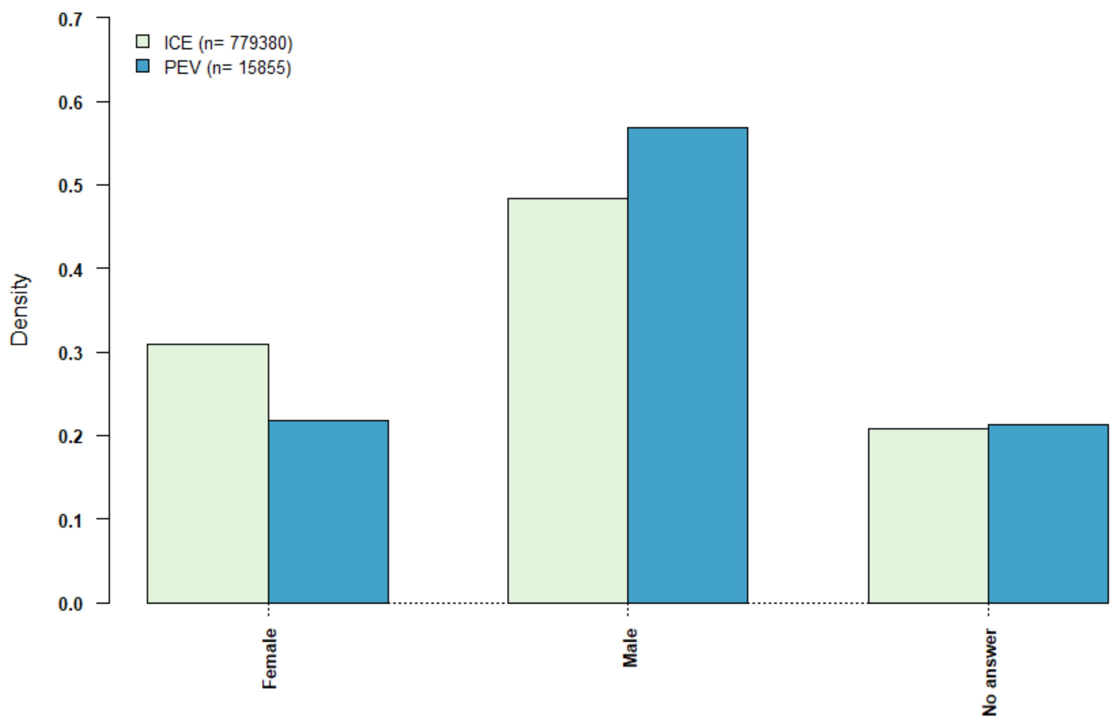

Figure 5. Gender distribution among buyers for two powertrains

Compared with ICE purchasers, PEV purchasers in our sample tend to be either very young or very old, wealthier, more highly educated, and concentrated in California. Table 4 contains the summary statistics after the matching. Because we used exact matching on state, education level, income bracket, and gender, the distributions for the matched data sets are identical.

Table 4. Summary Statistics of Matching

Question 1: PEV vs ICE *purchaser* satisfaction			Question 2: PEV vs ICE *considerer* satisfaction			Question 3/Question 4: Reasons for rejecting considered vehicle		
Counts by powertrain purchased (after cleaning)			Counts by powertrain considered but rejected (after cleaning)			Counts by powertrain considered but rejected (after cleaning)		
Gas	Plug-in Hybrid	Electric	Gas	Plug-in Hybrid	Electric	Gas	Plug-in	Electric
602,860	6,327	5,883	358,155	1,960	2,168	360,107	1,965	2,173
602,860	12,210		358,155	4,128		360,107	4,138	
After matching								
Number of paired matches observations: 11,987			Number of paired matches observations: 4,011			Number of unpaired matches observation: 36,736 Number of paired matches observation: 4,021		
Drops in treated group								
Number of drops: 223			Number of drops: 117			Number of drops: 117		
% of drops: 1.82			% of drops: 2.83			% of drops: 2.83		

For example, table 4 shows that 11987 PEV purchasers were matched with a similar person from the ICE purchasers group based on their age, gender, education, income and state. However, 223 people could not be matched with anyone from the ICE purchasers group based on our criteria.

The reason that the counts of considerers in question 3/question 4 is different from question 2 is that there were some people who did not respond to the satisfaction question and we had to eliminate them for question 2 but their responses can be used for question 3/question 4.

Since the control groups (ICE purchasers or considerers) are very large, it is possible to have several equally appropriate matches for each individual in the treated group. The matching() command in R was used to randomly choose one of them for Wilcoxon and McNemar tests. For chi-squared test the command was modified to return all suitable matches.

2.3.2 Consumer Satisfaction with Purchase Experience

Figure 6 shows the distribution of level of satisfaction for each group of purchasers with very little difference between the matched and unmatched samples. In the unmatched data, 26.8% of PEV purchasers reported satisfaction level 3 and below (somewhat satisfied to very dissatisfied), compared with 23.1% of ICE purchasers. In the matched data set, this difference is almost the same; 26.9% of PEV purchasers and 23.3% of ICE purchasers. The Wilcoxon signed rank test on the matched samples indicates that this difference is statistically significant (W = 1,701,600, p = 3.675 x 10^{-6}), indicating that we should reject the null hypothesis of no difference in satisfaction between similar PEV and ICE purchasers.

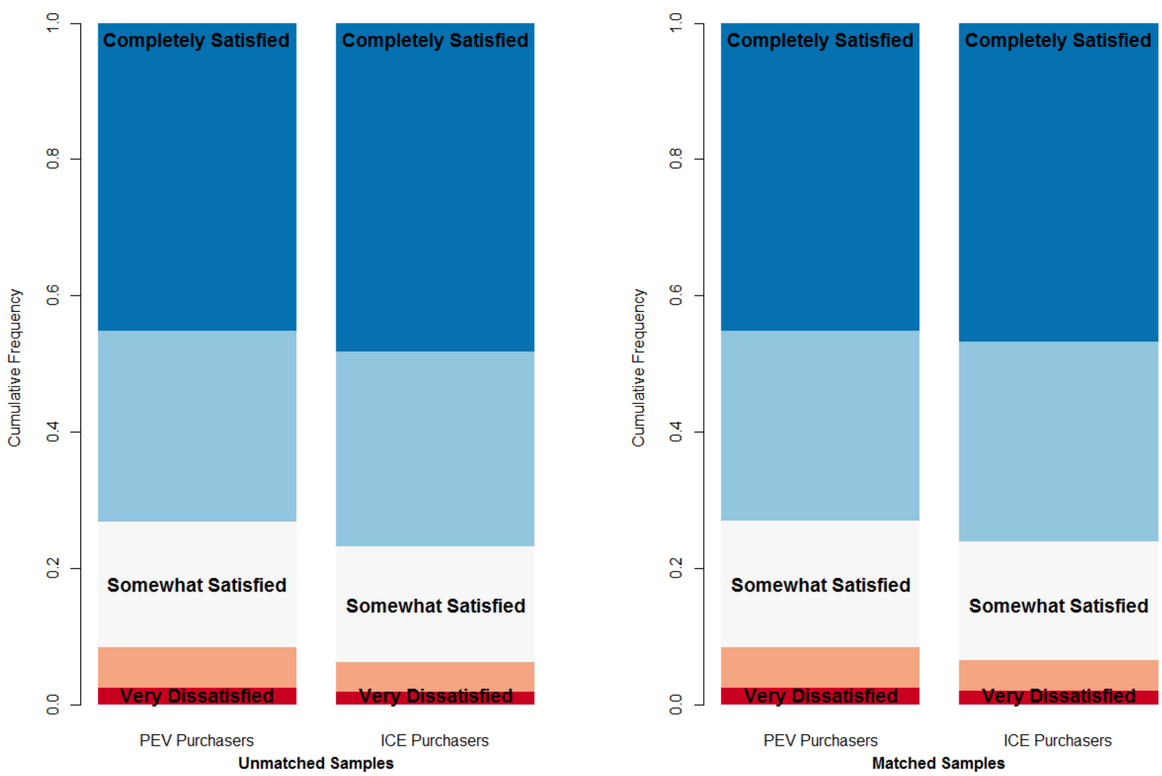

Figure 6. Cumulative frequency of levels of satisfaction for PEV purchasers and ICE purchasers

Figure 7 illustrates the distribution of level of satisfaction for those who considered but rejected a PEV, and those who considered but rejected an ICE. It shows that PEV considerers reported satisfaction level 3 and below (somewhat satisfied to very dissatisfied) more often than ICE considerers. The Wilcoxon signed rank test on the matched samples indicates that this difference is highly significant (W= 1,649,700, p = 0.0001284). As with the purchasers, the difference in satisfaction between PEV and ICE considerers is only slightly smaller in the matched pairs than in the unmatched data. There is a significant difference in satisfaction between those who considered but rejected a PEV and those of the same age, gender, education level, income category, and state who considered but rejected an ICE vehicle.

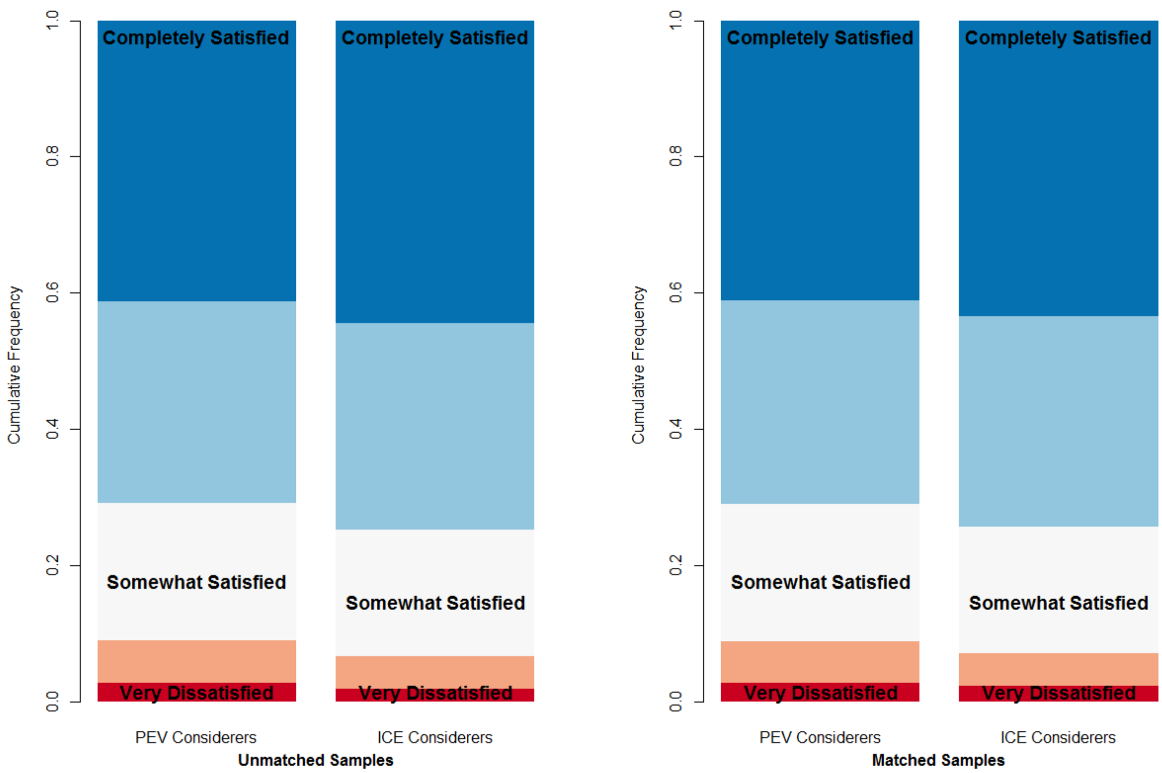

Figure 7. Cumulative frequency of levels of satisfaction for PEV considerers and ICE considerers

2.3.3 Evaluation of Reasons for Rejecting a Vehicle

To test whether consumers rejected PEVs for different reasons than they rejected ICE vehicles, we constructed matched pairs of PEV considerers and ICE considerers. After matching the two samples, we created 2x2 table for each potential reason for rejecting a considered vehicle. Some of the reasons were added to the survey after 2011. For example, environmental friendliness was added to the questionnaire in 2012 and seating capacity, country of manufacturer, and rear leg room were added to the 2014 questionnaire. Therefore, we have different numbers of total responses for them. After creating the 2x2 table for each of the reasons, we conducted the McNemar tests.

Table 5 provides both the p value of the chi-squared test and the mean p-value for 150 runs of the McNemar test. The Bonferroni correction is applied (0.05/27) to establish a critical p-value of 0.00185. Rejection reasons with p-value smaller than 0.00185 are highlighted in table 5.

Table 5. McNemar and Chi-squared Test Result for All the Reasons

Reasons	McNemar Result average *p*-value (150 repetitions)	Chi-squared *p*-value
Cargo Capacity	5.18E-03	2.04E-07
Riding Comfort	9.65E-02	6.50E-03
Attitude of Dealer Personnel	1.14E-06	1.56E-08
Ease of Handling	5.89E-02	2.21E-03
Exterior Styling	1.65E-01	4.14E-01
Interior Roominess	1.26E-01	1.28E-02
Interior Styling	6.85E-01	5.09E-01
Lease Option Not Available	3.50E-04	3.10E-09
Model Not Available at Dealership	4.86E-08	1.21E-21
Fuel Economy	7.11E-01	7.12E-01
Available Options/Equipment	6.90E-01	6.65E-01
Other	2.06E-03	3.11E-06
Engine Performance/Power	1.96E-01	4.38E-01
Price/Deal Offered	3.74E-02	1.06E-01
Overall Quality/Reliability	7.22E-02	2.56E-04
Financing Terms/Rebate	4.55E-02	2.43E-03
Manufacturer's Reputation	4.03E-01	1.30E-01
Safety Features	4.39E-01	5.80E-01
Communication System Not	5.01E-01	3.40E-01
Vehicle Size/Type	4.24E-01	9.22E-02
Future Trade-in/Resale Value	1.23E-03	1.13E-04
Value for The Money	2.47E-02	2.60E-05
Warranty Coverage	2.11E-06	1.30E-09
Environmental Friendliness	4.25E-04	9.19E-11
Country of Manufacturer	5.31E-01	1.05E-01
Rear Leg Room	4.54E-01	3.29E-03
Seating Capacity	1.23E-01	1.35E-05

Figure 8 shows the mean of the fraction of the respondents in matched samples who cited each reason for rejecting a considered vehicle. They are separated by type of powertrain considered. We report the mean of the 150 runs because the control group varies because of the random selection during matching step. The grey columns are the percentage of all the pairs that a PEV considerer chose that reason, and black columns are percentage of all the pairs that an ICE considerer chose that reason.

By looking at figure 8 and 9 we find out which reasons are important for each group in general based on frequency of citation.

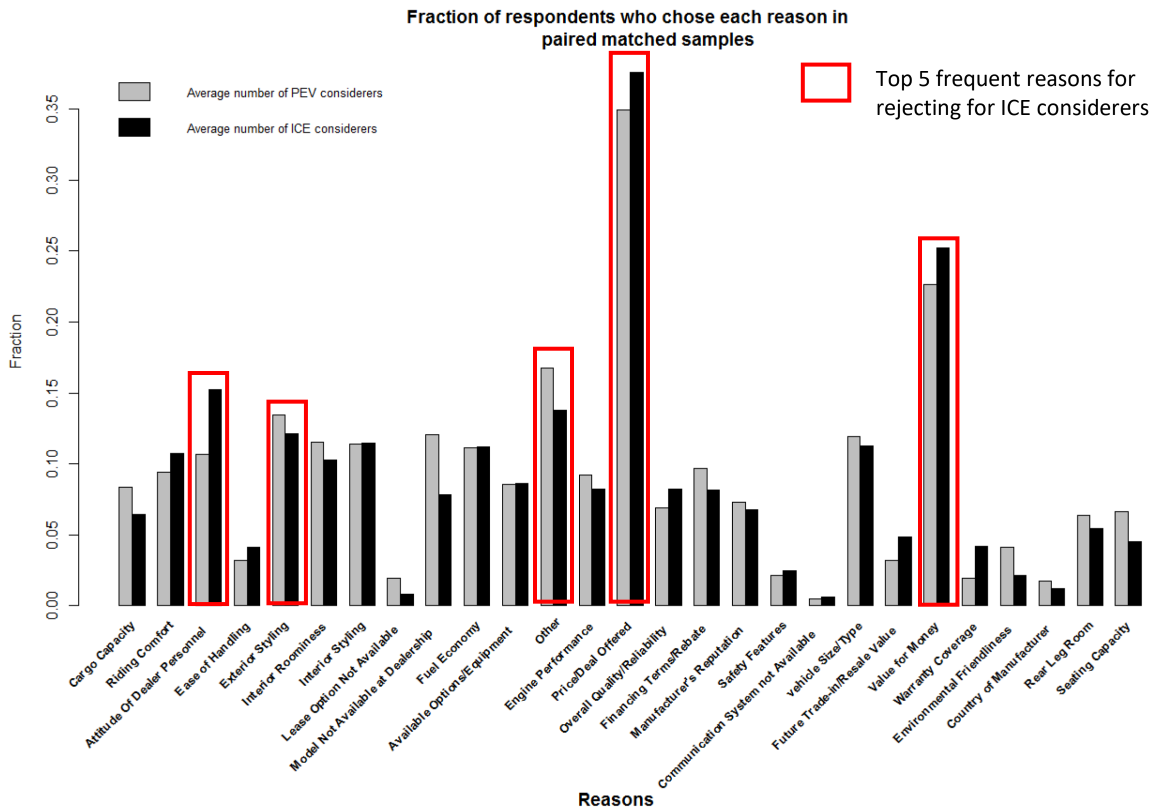

Figure 8. Fraction of respondents who chose each reason in paired matched samples (1 ICE considerer matched to each PEV considerer)

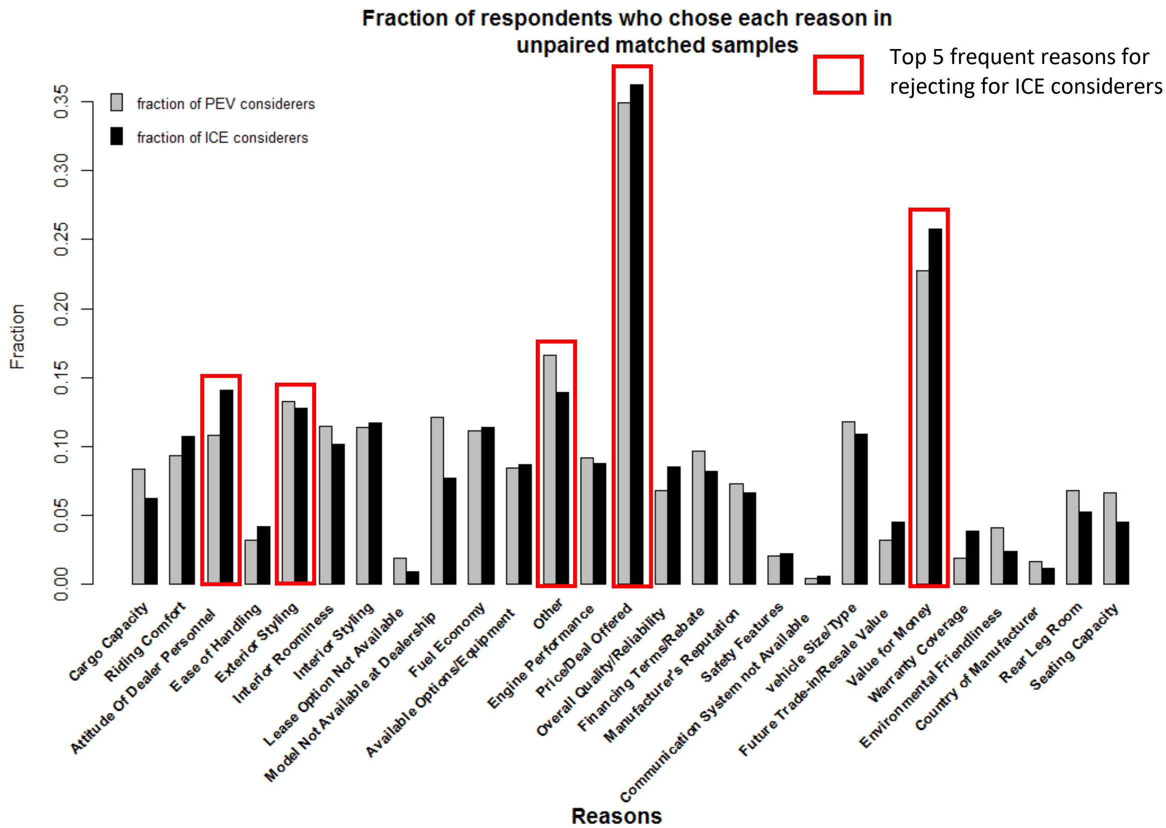

Figure 9. Fraction of respondents who chose each reason for unpaired matched samples (multiple ICE considerers matched to each PEV considerer)

There were 6 rejection reasons that were identified as significantly different for PEV and ICE considerers, based on both the chi-squared and McNemar test. In addition, based on the chi-squared test on the unbalanced data, there were 5 further reasons that were identified as significantly different for PEV and ICE considerers.

2.4 Discussion

There is a small but statistically significant difference in satisfaction between all PEV buyers and all ICE buyers in the sample. This could be due to differences in dealership experience, or to differences in PEV and ICE buyers' general propensities to be satisfied or not [46]. Because the samples were matched on covariates this suggests that the difference in satisfaction is indeed due to differences in the vehicle purchasing experience – although the difference appears to be small in practical terms, and might be attributable to other factors not tested, such as brand experience.

Since it is possible that a poor dealership experience could actually be turning people off from buying PEVs, we also examined buyers who considered but ultimately rejected a PEV, to see if they reported a lower level of satisfaction. The pattern of the consider-but-reject group was similar to the purchasers: those who considered but rejected a PEV were slightly but significantly less satisfied than those who had considered but rejected an ICE, and most of this difference persisted even after constructing matched pairs.

Also, from comparing figure 6 and figure 7 we can see that buyers who considered but rejected a PEV were not less satisfied (in a practical sense) than those who bought a PEV. Overall, these results suggest that PEV buyers are slightly less satisfied than comparable ICE buyers, but the difference is very small in practical terms, and it is unlikely that an unsatisfactory dealership experience is turning off potential PEV buyers.

The result of the McNemar and Chi-squared tests indicates 6 reasons that are significantly different between ICE and PEV considerers, and 5 that may be significantly different based only on the Chi-squared test. Out of these 11 reasons “attitude of dealer personnel” and “value for the money” are among important rejection reasons for ICE considerers and they cited these reasons more often than PEV considerers. Even though both PEV considerers and purchasers are less satisfied with their overall purchasing experience at the dealership, “attitude of dealer personnel” was reported significantly more often by similar ICE considerers as an actual reason of rejecting a vehicle.

“Price/deal offered” is cited most often as a reason for rejecting a vehicle for both groups. Based on this, price does not appear to be a disproportionately important barrier for those who reported seriously considering a PEV between 2011 and 2015. However, it is possible that perceptions of high prices or poor relative value for PEVs precluded some consumers from seriously considering a PEV in the first place. In other words, price and value could be an important barrier, especially for the general vehicle consumer who, as shown in figure 2 has a lower income and in general is more price sensitive. This will be a bigger problem long-term if price reductions do not exceed the lost value from depleted financial subsidies or other incentives such as HOV lane access that improve the value of a PEV.

Among the top 5 rejection reasons cited by ICE considerers, “other” is the only one to be cited more often by PEV considerers. Reviewing the “other” reasons written by consumers, limited range is commonly listed among them. Although we don’t know whether it is significantly more important than other mentioned reasons based on our data, previous research confirms that range anxiety can be a major concern of consumers about electric vehicles [59, 60].

PEV considerers were significantly more likely than ICE considerers to cite “model not available at dealership” as a reason for rejecting a vehicle. This is surprising, since dealers are generally willing and able to order a vehicle from another nearby dealership, even if it is not available on the same dealer's lot. Nevertheless, it may be important, though we should be careful about what this does and does not tell us. One possible explanation is that consumers may consider a test drive to be more important for PEVs than for ICEs, due to the novelty of the powertrain. Even if PEVs are just as common on dealer lots (or more so) as ICEs, consumers may be more inclined to stop considering the PEV in those cases when the PEV is not available. Another explanation is that, to the extent that PEV sales volumes are lower than conventional vehicle volumes, this would tend to increase the inventory costs of keeping PEVs on the lot. As sales volumes for PEVs increase, we expect it to become easier for dealerships to make sure they have at least one or two PEVs on the lot at all times. Either of the above reasons would be expected to resolve itself in the future, as familiarity with the technology increases and the market grows. However, for now it could negatively affect PEV considerers' perceptions of the vehicles and market growth, but the extent needs further evaluation.

Interpreting table 5, figure 8 and figure 9, PEVs' models and styles, the availability of models and lease option, and "other" reasons are issues that PEV considerers are concerned with more often than ICE considerers. We conclude that other main barriers to converting PEV considerers into purchasers are limitations in the vehicle attributes such as variety and availability of models, and "other" reasons including range limitations.

It is surprising to see "Environmental friendliness" cited more often as a reason for rejecting PEVs than for rejecting ICEs. One possible explanation is that consumers who are considering a PEV may initially expect it to be cleaner and greener than it is. Another possibility is that these are consumers who rejected a PHEV in favor of a BEV. Finally, some respondents may simply cite this as an excuse for not purchasing the vehicle. Regardless, we note that the overall importance of this reason is fairly low (cited by less than 5% of respondents), which is consistent with prior research [59] finding that a history of pro-environmental behavior was less important than fuel savings in determining choices of PEVs.

This analysis has provided a new perspective on the PEV purchasing experience. Our results suggest that current PEV purchasers are less satisfied with the dealership experience than similar ICE purchasers, by an amount that is statistically significant but likely of little practical consequence. This result is consistent with findings of prior research [42], although our methods differ (matching vs. regression). We also go further than prior work, finding a similar gap in satisfaction between those who considered but ultimately rejected a PEV, and those who considered but rejected a conventional vehicle. We believe the latter comparison is more relevant to the question of whether a poor dealership experience is turning customers off of PEVs. Our analysis of consumers' reasons for rejecting PEVs and conventional vehicles suggests that attitude of dealer personnel is not an important determinant of the decision to reject a PEV. Therefore, policy specifically targeting dealer education may not be effective, as the underlying reasons have more to do with the overall value proposition as determined by the attributes, price, and availability of PEV models.

2.5 Limitations and future research

The application of matching methods to our large data set provides excellent internal validity, but the early stage of the PEV market limits this study's external validity (i.e. its generalizability to a constantly-evolving PEV market). The data include automotive sales from 2011-2015. Even though the PEV data is skewed towards the later years (table 1) at the beginning of this period both technology and variety of PEVs were limited and through these years many improvements in PEV technologies and accessibility of charging facilities occurred while regulators were working toward incentivizing PEV purchasing. Therefore, it may be worthwhile to do a similar analysis in several years to explore the impacts of the next generation of PEVs and fuel cell vehicles.

While this work has addressed both dealership satisfaction and reasons for rejecting a considered vehicle, it has not done so in a unified fashion. In the future, methods such as hybrid choice modeling [61] might allow us to understand how satisfaction, rejection reasons, and observable vehicle attributes interact to shape choices, particularly as the PEV market matures and the repurchasing patterns of PEV buyers become available. In particular, this would allow us to test quantitatively our judgment that the difference in satisfaction between PEV and ICE considerers is of little practical importance.

There are additional aspects of the dealership experience that may affect consumers' satisfaction and their selection or rejection of a PEV. Our data set included "attitude of dealer personnel" and "model not available at dealership" as potential rejection reasons. However, other relevant factors might include things like "sales staff knowledge of product" or "availability of product information."

The need for statistical robustness limited cutting the data in additional ways, but this may be possible in the future as cumulative and annual PEV sales grow. For example, in this analysis we did not match using premium vehicles vs. non-premium, or by brand. This may influence the level of satisfaction of consumers since premium vehicles' dealerships and brands provide different purchasing experience for the customers, but most of the PEVs in the study were purchased through a few non-premium brands. The next step would be to match the consumers based on whether they purchased a premium vehicle or not, or by specific brand. Additionally, while income was used for matching, the value of that income does vary by geographic location within state based on cost of living. This affects ability or willingness to spend on a vehicle.

This research specifically evaluated the decision factors after a consumer has put a PEV in their consideration set. It would be valuable to conduct a parallel analysis of potential consumers who are familiar with the technology to determine if the same reasons for rejection also are important influencers in moving consumers from being merely familiar to actually considering a PEV.

Chapter 3: EV everywhere or EV anytime? Co-locating multiple DC fast chargers improves both operator cost and access reliability.

Acknowledgment

This chapter is based on a paper jointly authored with Don MacKenzie, presented at Transportation Research Board, No. 17-05991.

3.1 Background

As described in chapter 1, there are many barriers on the way of battery electric vehicles (BEVs) adoption. Based on chapter 2 and other literature in this area, we know adoption is highly depended on factors such as up-front cost, fuel cost, charging time, and the availability of charging infrastructure [29]. In chapter 2, the analysis of rejection reasons confirmed that still technological limitation including range anxiety is one of the important reasons that consumers reject electric vehicles. Lack of public charging infrastructure is another contributor to this anxiety. Figure 10 illustrates that over 60% of initial BEV adopters charged more than once per day on average. Between this and the fact that not all drivers have access to home charging facilities [62] the necessity of public charging facilities is clear.

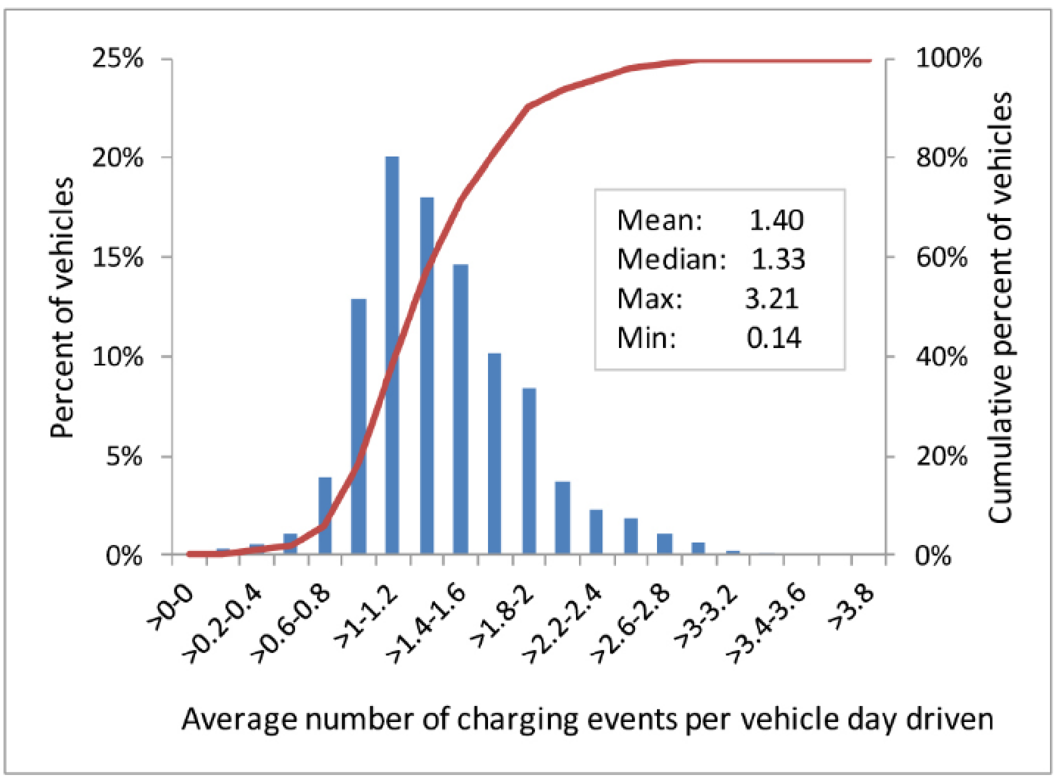

Figure 10. Distribution of daily average charging events across battery electric vehicles in the EV Project [63]

Fast chargers help to address charging time issues by reducing charging time to around 30 minutes. Botsford and Szczepanek [64] concluded that the availability of DC fast chargers would increase adoption of BEVs considerably. Fontaine [65] calls fast charging infrastructure a "catalyst" for consumer acceptance of BEVs. A study of the usage of charging infrastructure in Ireland has shown higher charge consumption values and charging frequency for fast charging infrastructure than standard ones [66].

Widespread deployment of public DC fast charging infrastructure therefore appears necessary both to ensure that BEVs can meet drivers' travel needs from a technical standpoint, and to increase consumers' willingness to adopt BEVs. Building charging infrastructure in more locations can help to address range anxiety, but is not sufficient to ensure reliable recharging access. Reliable charging access requires not only that chargers are deployed in enough locations, but also that a charger is available when a driver needs to use it.

Installing and operating DC fast chargers is expensive, and in order to justify these costs, DC fast chargers need to achieve a high rate of utilization. Work commissioned by the EV Project [67] explores the effects of utility demand charges on the costs of operating a DC fast charging, and how higher utilization could help to reduce those costs. On the other hand, to make BEVs appealing for users, the price of charging needs to be kept as low as possible, and reliable access to charging is a must. This sets up a fundamental tension: infrastructure developers would like to see infrastructure being utilized more of the time, but when a charger is in use, it is not available for other drivers.

In this chapter, we study the interactions among utilization, availability and cost of DC fast charging infrastructure. We develop a queueing model to characterize the tradeoffs between utilization and availability of charging stations, and how these tradeoffs become less severe as the number of vehicles served increases. We also show that when we consider the need to maintain reliable access to charging, it becomes much more challenging to grow the BEV market to the point where investments in DC fast charging infrastructure are financially viable.

3.2 Queue Model

Queuing theory analyzes the relationship between the demand for specific service and the availability of that service for the users. "A *queueing system* is a generic model that comprises three elements: a user source, a queue, and a service facility that may consist of one or more identical servers in parallel" [68]. The user source generates users who pass through the queue into the service facility. Each user spends a specific amount of time, ranging from zero to infinite in the queue. When the user has left the server and is no longer using it, we consider that user has left the queuing system. In the case of a DC fast charging station, the user source is BEV drivers who wish to charge, and the servers are DC fast chargers, of which there may be one or more at any given charging station (the service facility). Three sets of information are required to model a queueing system:

1. The user generating information (The time between when they arrive at the service facility)
2. The queue discipline (The order in which users enter the service facility)
3. The service process (The time needed for a server to service a user).

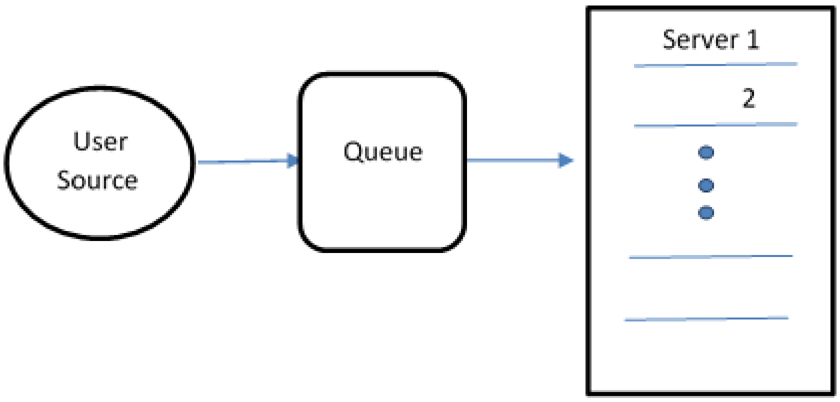

Figure 11. Scheme of Queue Model

We assume that users' arrivals and departures follow Poisson processes, so the interarrival time and service time follow negative exponential distributions [69]. This is known as an M/M/m queue model in which the M's indicate Poisson arrivals and departures, and m represents the number of servers. The service times for each charger are assumed to be independently and identically negative exponential distributed. The queue discipline in this model is first come, first serve: when all the servers are busy, the user who has been waiting the longest will be assigned to the first server that becomes available.

The key outputs from our model are availability and utilization. We define utilization as the fraction of time that the chargers are in use. If the rate of arrivals of users is given by λ and μ is the average service rate for one server, then utilization ratio, ρ, is calculated as follows:

$$\rho = \frac{\textit{rate of user arrivals at the service facility}}{\textit{total available rate of service}} = \frac{\lambda}{m\mu} \qquad (1)$$

3.2.1 Assumptions

We define availability as the probability that at least one server would be available when a user arrives (so the user does not have to wait to charge). This is the probability of the queuing system being in a state less than *m*, where *m* is the number of servers.

To parameterize our model, we used typical characteristics of current BEVs and DC fast chargers. In this model, the inputs are the number of servers, charging time and arrival rate, and the outputs are utilization and availability.

Researchers in the EV Project reported that charging time for a Nissan Leaf (a popular BEV), from 30% to 80% state of charge, is around 25 minutes [70]. Here, we assume a charging time of 30 minutes. Also, most DC fast charging activity happens between 11 a.m. and 11 p.m. [70]. Therefore, we assume that stations are active for 12 hours per day and arrival rates are constant in that time frame.

3.3 Business Model

We develop an illustrative application of how the results of the queue model and consideration of charger availability can be incorporated into a business case analysis. We explore how number of vehicles served per month impacts the attractiveness of an investment in a DC fast charging station, as measured by the net present value of the project. In order to do so, we assume a project life of 10 years and a discount rate of 15%. The results are sensitive to assumptions, of course, but the objective is to illustrate the general direction and magnitude of the effect that maintaining reliable access has on profitability. Therefore, results are not intended to be precise or predictive.

3.3.1 Costs

We based our capital and maintenance cost estimates on BMW's recent installations of DC fast chargers in Seattle. We assumed that cost of purchasing each charger is $7000, with an installation cost of $2000 for the first charger and $1000 for each additional charger at the same site. We also assume $300 for shipping and handling per server. These costs are incurred at the beginning of the project. We assume maintenance costs of $1700 per charger per year, incurred annually. Finally, we assume 9.6% for tax on these costs. These costs are much lower than many other contemporary cost estimates, and are probably optimistic in the context of high-power DCFC installations along a highway corridor. This only reinforces our point that it is very difficult to get to the point where selling electricity through a DCFC station is an attractive investment.

Other important costs are those charged by the electric utility, which include meter charges, demand charges and energy charges. A meter charge is meant to cover the costs of maintaining lines, reading meters, billing and similar costs, and it is assumed to be $200 per month per *charging station* [68,71]. A demand charge is a fee proportional to a facility's maximum power draw over the course of a month. Here, we assume a demand charge of $600 per month per charger [68]. The energy charge is based on the amount of energy drawn and is assumed to $0.11 per kWh. Following the EV project [68], we assume that each vehicle's energy usage is 20 kWh per charging event.

3.3.2 Revenues

We assume that a charging station operator bills based on energy charged, with a price per kWh determined from the distance-equivalent price for gasoline. This is based on an assumption that to keep BEVs competitive with conventional vehicles, the cost for fast charging should not exceed the cost of gasoline on a per-mile basis. We assume that the price of one gallon of gasoline is $2.00, which is close to the U.S. average reported by the Energy Information Administration for the first half of 2016. We use the 2015 Nissan Versa and 2015 Nissan Leaf as a basis of comparison. The Versa averages 32.4 miles per gallon, which works out to about $0.06 per mile [72]. The Leaf on average consumes 0.3 kWh per mile [72]. In order to keep the per-mile energy cost of the Leaf less than that of the Versa, a charging station operator should not charge more than $0.20 per kWh.

In addition to billing for energy, there are other potential revenue sources for a DCFC station operator, through activities such as partnerships and sponsorships, energy premiums and value-added services [71]. As we will see, such revenue sources are probably crucial to making the economics of DCFC stations viable in the near term.

3.4 Results

3.4.1 Queue Model

We begin by presenting the tradeoff between utilization and availability in charging station operations, and how this changes as more servers are added to the system. When there is only one server in the system, there is a direct linear tradeoff between utilization and availability. If a charging station has only one charger, and it is utilized 30% of the time, then it is (of course) only available 70% of the time. However, when multiple servers are available in the same system, higher levels of utilization can be realized while maintaining a given level of availability for users (and vice versa). Figure 12 illustrates the relationship of utilization and availability and how number of servers impact this relation. By adding more servers, it is possible to improve both utilization and availability: achieving a win-win situation for both the operator and the users.

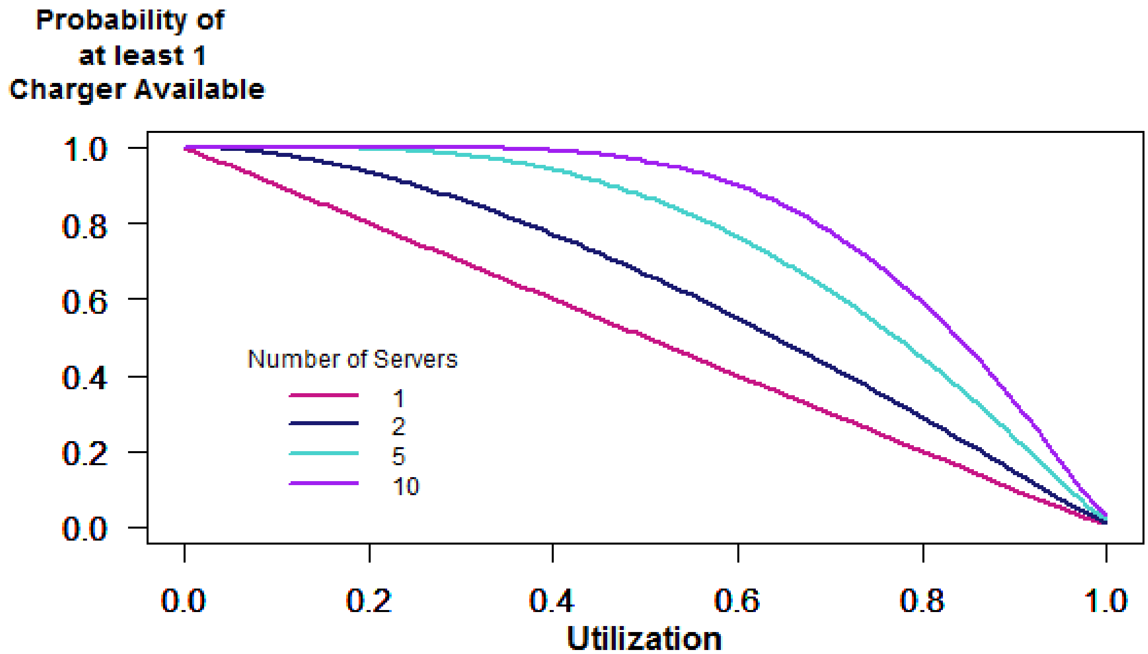

Figure 12. Effect of co-locating multiple servers on availability - utilization trade off

Next, we determined how many servers were required to maintain a certain minimum level of availability as the number of vehicles served increases. We assumed that there is some threshold level of availability that we wish to maintain. For example, we might want to ensure that a vehicle arriving at a random time would find a charger available with 90%, 95% or 99% probability. Figure 13 illustrates the relationship between average arrival rate, number of chargers per station, and the probability of at least one charger being available at a random time. For a given average arrival rate, a higher target availability level means more chargers are needed at each station. Also, as average arrival rate increases, more chargers are needed to maintain a given level of availability. The flat “steps” in Figure 13 reflect the fact that a given number of chargers can maintain a target level of availability for a range of arrival rates, but when the arrival rate exceeds that range, another charger must be added. A final important feature of Figure 13 is that the required number of chargers increases less than linearly with the arrival rate, with each additional charger adding a larger increment to the allowable arrival rate (i.e. the “width” of the steps increases as arrival rate increases).

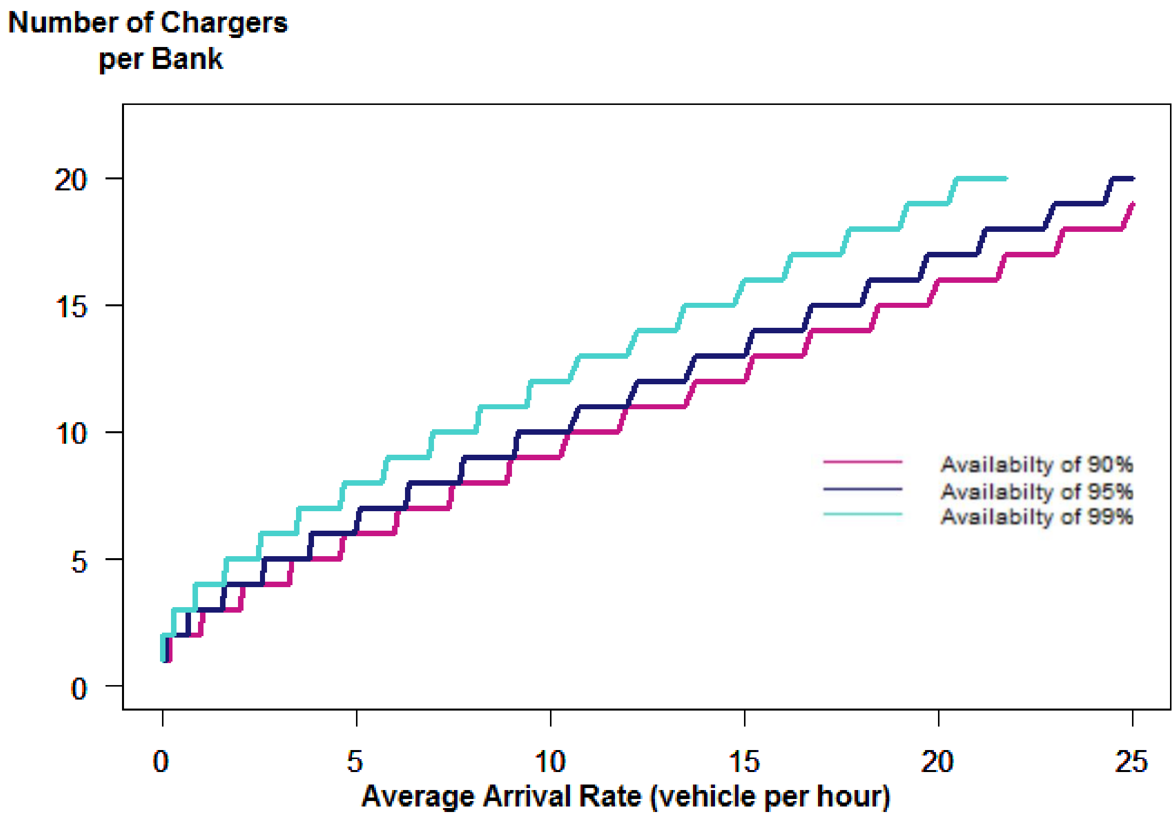

Figure 13. Effect of availability on number of chargers per bank as average arrival rate increases

Figure 14 plots the utilization rate of chargers as a function of the monthly number of vehicles served by a charging station. The “sawtooth” pattern in utilization results from adding more chargers: each time a new charger is added to a charging station to maintain availability, the overall utilization of chargers at that station drops. Generally, however, as the market grows, more plugs are needed but each plug has higher utilization. Yet it can be seen that to achieve 30-50% of utilization, more than 2000 vehicles need to be served per month. Also, based on the relationship between utilization rate and number of vehicles served per month, it can be seen that improving utilization rate demands great growth in the BEV fleet. Maintaining satisfactory availability therefore makes it harder to improve utilization rate.

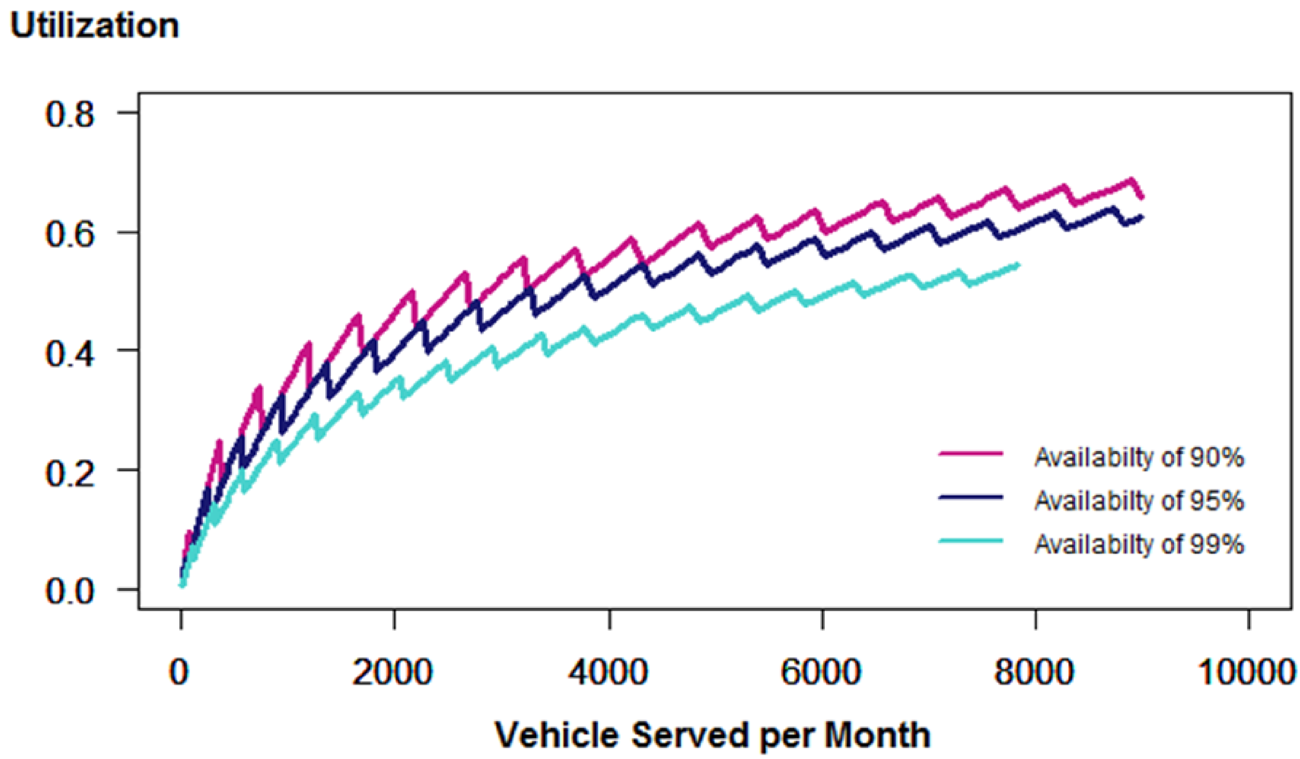

Figure 14. Effect of availability on utilization rate as number of vehicles served per month increase

3.4.2 Business Model

We begin with a simplistic model that does not consider reliability of access (availability) for a charging station. We assume that each charge takes an average of 30 minutes, and the charging station is active for 12 hours per day, so each server can serve 24 vehicles per day. Under these assumptions, the net present value increases rapidly with the number of vehicles served, as shown in Figure 15. Net present value increases as more vehicles are served, up to the point that capacity is saturated, and another charger must be added.

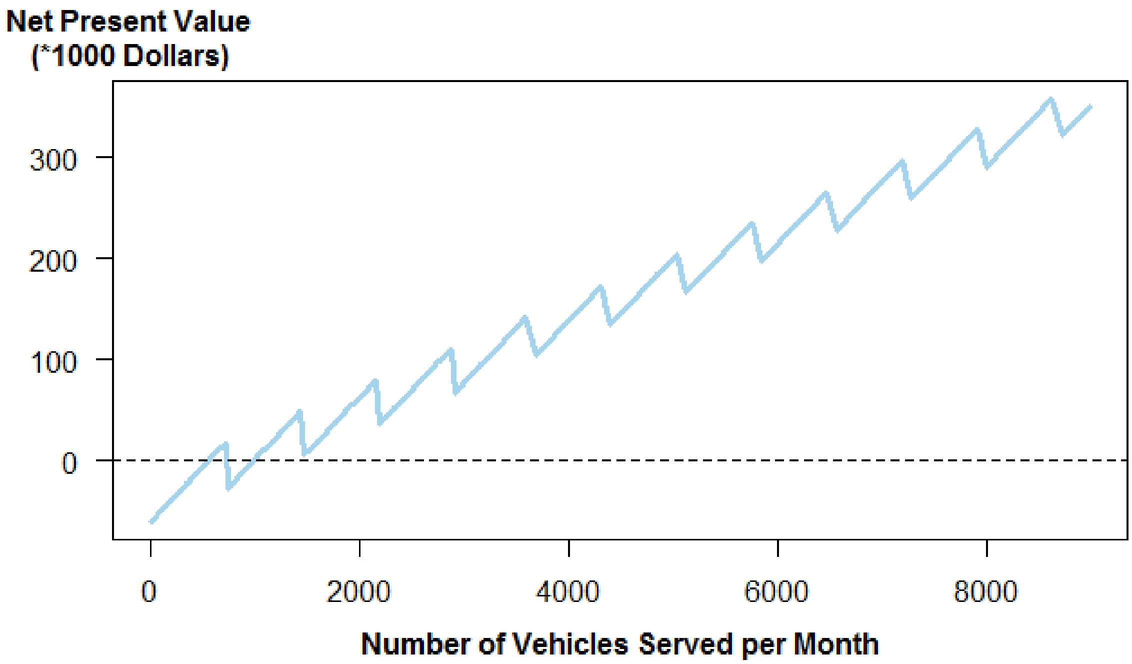

Figure 15 Impact of number of vehicles served per month on net present value when availability is not considered

However, this is not realistic. Since people arrive at the stations randomly, some of them would have to wait in queue for a long time. This inconvenience and inadequacy of service for the users would cause them to not come back again, while unreliable fast charging access would also likely curtail demand for BEVs among vehicle purchasers. Therefore, Figure 15 does not represent a viable path to growing the PEV market or profitably deploying infrastructure.

Figure 16 illustrates the effect of maintaining reliable access to chargers. To maintain availability, more servers need to be added as the BEV fleet grows, well before capacity is fully utilized. Once again, the sawtooth pattern in the plot is caused by adding servers each time availability drops below the specified target level. It can be seen that up to a point, adding more vehicles to the system actually decreases net present value. This is because the cost of adding servers to the system to maintain availability is higher than the revenue earned. The higher the target availability level, the more significant this effect is. For example, for an availability of more than 80%, the decrease in net present value is almost negligible. However, if we want to maintain availability of more than 95% we can see a decreasing trend in net present value for the first 1800 vehicles per month. This is because the cost of adding a server is greater than the incremental revenue from the additional customers. As demand gets sufficiently large (above 4000-8000 vehicles per month, depending on the target availability level), the net present value becomes positive. However, the high costs of fast charging stations and the need to maintain reliable access create a "valley of death" for fast charging market growth.

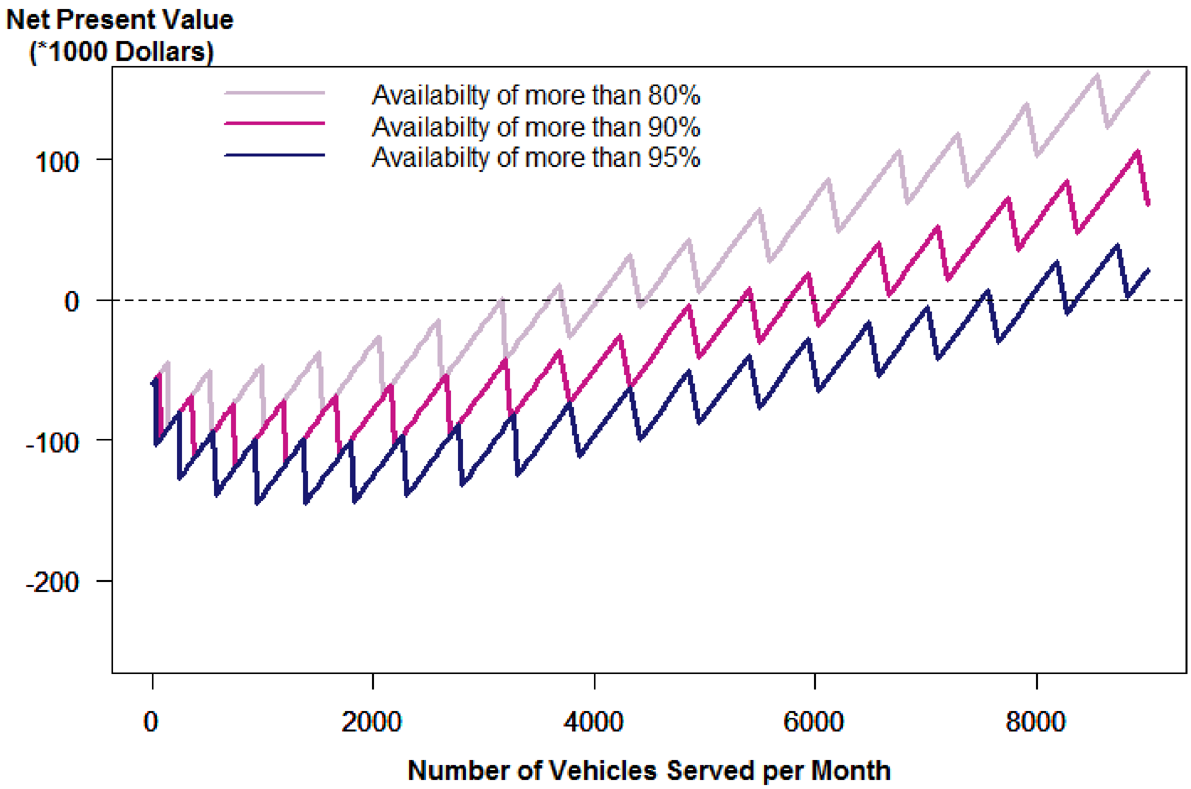

Figure 16. Effect of number of vehicles served per month on net present value for different levels of availability

Figure 17 shows the breakeven number of vehicles that must be served (that is, the minimum number of monthly vehicles served that will generate a positive net present value), as a function of the target availability level. It suggests that the breakeven number of charges per month is very sensitive to the required level of availability, particularly at high levels of availability. This suggests that more research should be done to identify precisely what an acceptable level of availability is for current and prospective BEV owners.

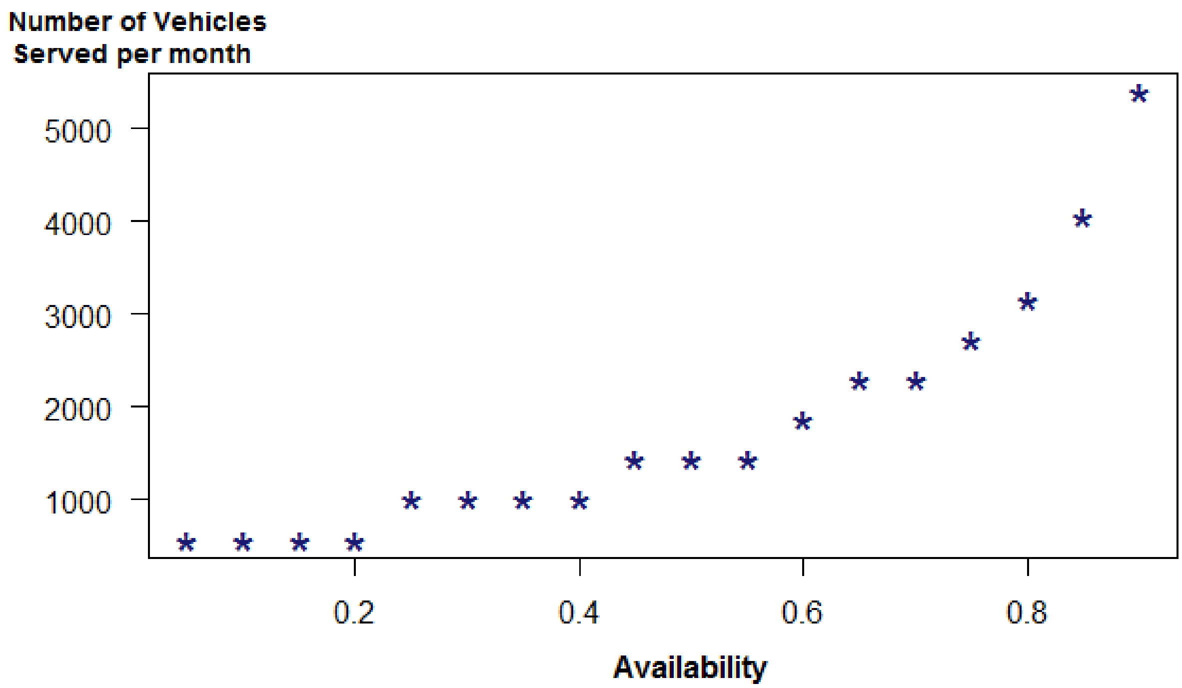

Figure 17. Minimum volume required to provide positive net present value, for each level of availability

3.4.3 Software Application

Since our analysis is based on assumptions and some of these assumptions varies with time, geographical location and advances in technology we have created a RShiney app [76] to help planners, policy makers or anyone who is interested in this topic to input their own assumptions and explore how net present value will change as market grows based on their assumptions. They can also use this tool to explore the impact of availability on utilization. Figure 18 shows a snapshot of the app and its inputs and output.

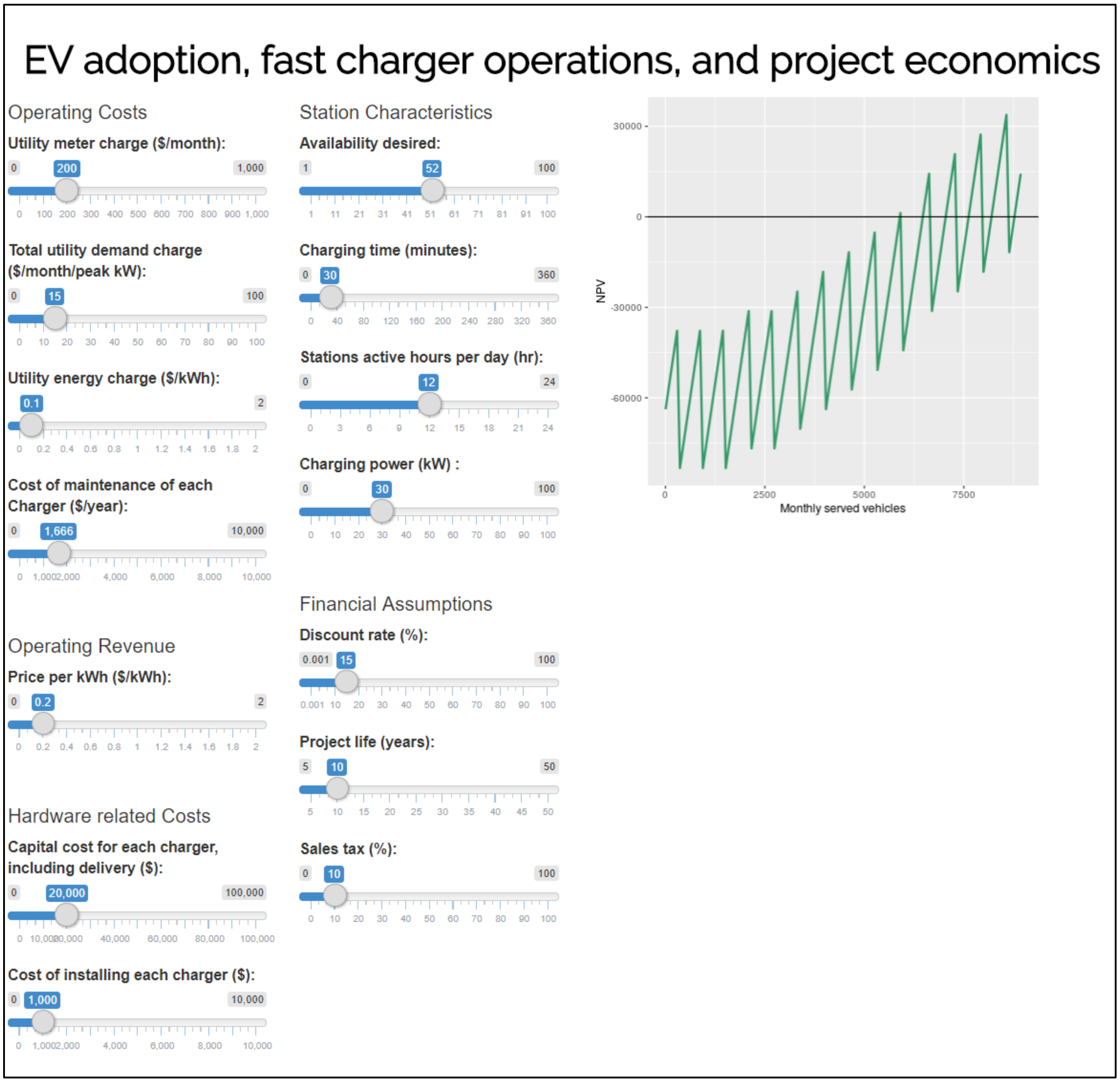

Figure 18. snapshot of the application for exploring tradeoffs of EV adoption, fast charger operation and project economics. https://queueingmodel.shinyapps.io/queueingapp/

3.5 Discussion

DC fast chargers have high capital and fixed costs, so to be cost effective they need to have high utilization. In order to provide users with reliable service and reduce their range anxiety, a satisfactory level of charger availability should be maintained. Installing an excess of DC fast chargers is one way to ensure availability, but it leads to low utilization of the chargers if the demand does not increase. However, as the BEV market grows, both utilization and availability can be improved if larger numbers of DC fast chargers are co-located at stations.

Our findings illustrate how the need to maintain reliable access limits the degree of utilization that we can get out of charging stations in the near term. This suggests that it will be even harder than previously thought to reach the stage where there is clear business case for DC fast charging.

Decision makers can use this model to estimate the number chargers per station required to balance the availability of chargers and utilization rate in order to provide satisfying service for users and beneficial business for operators. Also, this model demonstrates how growing the fleet of BEVs can lead to more affordable cost of charging for users and higher utilization rates for stations' operators.

As discussed in the business model section (3.4.2), in order to provide higher quality of service for users, more vehicles need to be served so that costs and revenue break even and investors earn their money back and profit. Even though our specific assumptions are debatable, the qualitative impact of considering the reliability vs utilization tradeoff will remain; maintaining more reliable access will mean lower NPV**.** For example, to maintain availability of 80% and more, more than 5000 vehicles need to be served per month for the specific station in order to achieve a positive net present value over 10 years. Let's see how many BEVs the fleet need to have in order to serve the customers adequately and provide a return to the investors. Figure 19 from Greene [73] indicates that if percentage of stations offering an alternative fuel drops below 25%, the probability of choosing a car with that alternative fuel drops precipitously.

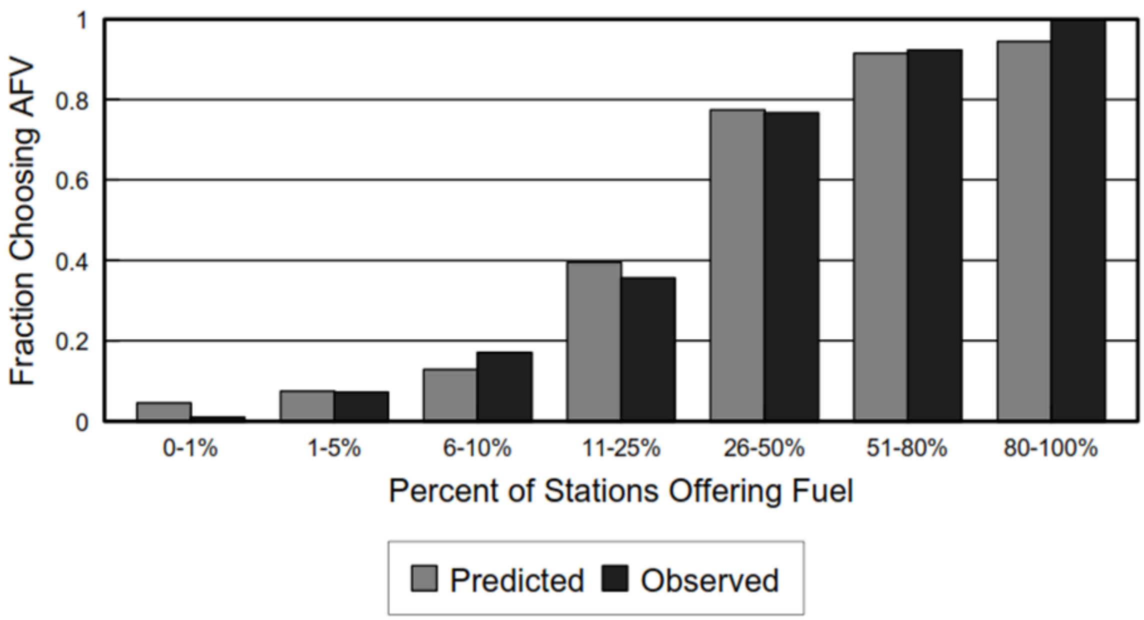

Figure 19. Cumulative frequency fit of exponential fuel availability model of alternative fuel engine choice [73]

Setting the number of DC fast charging stations equal to 25% of the number of gas stations in the U.S. implies 42,000 fast charging stations [72]. If station operators are to ensure that 80% of arriving BEV owners do not need to wait to charge (i.e. availability of 80%), about 4000 vehicles per station per month will be required in order to break even. If we assume that BEVs average one fast charge every 3 days (10 per month), then we would need around 17 million BEVs in the U.S. to ensure availability of 80% for drivers and an attractive investment for infrastructure developers. The situation can get even more challenging. As technology advances, the range of electric vehicles is expected to increase, and people would need to charge their vehicles less frequently.

There are several ways that these challenges might be addressed. For one, instead of focusing on the probability of zero waiting time, it might be useful to find out what would be the acceptable range of waiting time for users. This can help operators achieve better utilization without impacting quality of service dramatically.

Second, greater use of information technology, such as connected vehicles and reservable charging stations, could help to increase utilization while maintaining a good experience for drivers. Relatedly, we should aim to have chargers be compatible with all BEVs, either through mandating a single charging standard or ensuring that equipment is compatible with multiple standards. Failure to do so effectively reduces the number of chargers available, leading to lower reliability and less attractive investments.

As demonstrated in our business model analysis, capital costs of charging stations and utility demand charges are important components of total costs. By lowering these costs, investing in DC fast charging stations would become more appealing for operators. Providing subsidies for purchasing charging equipment is one way that can positively impact the capital cost, but would be extremely expensive to deploy at large scale. Also, as the BEV fleet grows more chargers will be produced, which could lead to cost reductions through learning over time [74]. However, some believe that these costs would not be strongly affected by scale since chargers mainly consist of less sophisticated electronics and standard commodities for the body, which are less sensitive to scale [75].

Finally, government and public utility companies can work on reducing utility demand charges. Even if it this cost reduction took place for a limited period of time until BEV fleet grows to the point that investors earn their money back, it could work as incentive and motivator for private sector investment.

We recommend that future work investigate how the utility of BEVs to current and prospective adopters depends on waiting times for fast charging, in order to establish appropriate targets for availability and waiting times. In addition, more sophisticated queuing models should be developed to capture the dynamic (not just steady state) operations of DCFC stations, while incorporating more realistic distributions of arrival and service times.

Chapter 4: Conclusion

This thesis seeks to improve understanding of market scale role in EV adoption by investigating consumers behavior toward purchasing EVs and infrastructure utilization tradeoffs with reliability of the facilities.

In the first chapter we looked into the background of electric vehicles, from their invention to their rise and falls during time, their advantages and why there is a need for their widespread adoption. Then we discussed the barriers existing on the way of EV adoption and prevent them from meeting goals and expectations. The most important barriers based on literature are range anxiety, lack of public charging infrastructure, high costs and unfamiliarity of users. Even though, several actions for addressing these barriers were taken, it seems they were not enough to achieve EV sales goals. Therefore, we explored consumer and infrastructure perspective in next chapters to find what is the reason for falling short of goals and projections.

In chapter two, we took a deep look in what turns off consumers who want to adopt a PEV. We found out that PEV buyers and considerers are less satisfied with their purchasing experience compare to similar ICE buyers and considerers. This dissatisfaction is significant in statistical terms but in practical terms seems to be minor. Also, we looked into reasons for rejecting a PEV and we didn't find dealership experience as statistically significant reason for rejecting a PEV. Interestingly, we find out ICE considerers are more concerned with dealership experience compare to similar PEV considerers.

In addition, the result of our analysis shows that, PEV and ICE considerers are equally concerned with "Price/deal offered" in statistical terms. For both groups, price and deal offered is the most cited reason for rejecting a vehicle. This is an interesting finding and needs extra attention since currently there are several incentives for purchasers, especially in the states that the majority of PEV buyers and our sample respondents are from. The price issue will be a bigger problem long-term if incentives are no longer available and price reduction of EVs do not exceed the lost value from depleted financial subsidies.

"Other" reason was cited most often by PEV considerers. Reviewing the "other" reasons written by consumers, limited range and charging infrastructure are commonly listed among them. Although we don't know whether it is significantly more important than other mentioned reasons based on our data, but it is consistent with what literature and previous research suggests.

PEV's models and styles, the availability of models and lease options are other reasons that PEV considerers are more concerned with compare to ICE considerers. Detailed interpretation of the results is provided in discussion section of chapter two.

The results from chapter two analysis suggest that even with existing incentives, the limitations of the current technology (e.g. price and range), lack of charging infrastructures and variety of available vehicles are the most important challenges to market expansion. However, we can expect that most of these barriers will be resolved with market growth.

In chapter three, we addressed the issue of range anxiety and lack of reliable public charging infrastructure and explored how they interact with facility utilization and market scale. We discussed that based on literature and evidence, DC fast chargers are required to provide consumers with reliable service. However, cost of DC fast chargers is high, and they need to have high utilization to be cost effective. We built a queue model informed by the characteristics (e.g. charging rates, battery size, range) of current BEVs and available DC fast chargers to determine how we can expect costs, utilization and availability of chargers to change with respect to each other and market growth and to find out what the costs are for maintaining satisfying availability for users. Our findings illustrate how the need to maintain reliable access limits the degree of utilization that we can get out of charging stations in the near term. This suggests that it will be even harder than previously thought to reach the stage where there is clear business case for DC fast charging.

The main insight from this thesis is that, among those who are considering buying PEVs, price, range anxiety, lack of charging infrastructure and lack of variety of models are turning them off. There need to be extra focus on these areas in order to meet the goals of EV adoption. Also, decision makers can use our queue model and application tool [76] to estimate the number chargers per station required to balance the availability of chargers and utilization rate to provide satisfying service for users and beneficial business for operators. This model demonstrates how growing the fleet of EVs can lead to more affordable cost of charging for users and higher utilization rates for stations' operators. This study concludes that market growth can address EV adoption barriers both for consumers and infrastructures.

References

[1] *History of Electric Car*, Office of Energy Efficiency & Renewable Energy, https://energy.gov/articles/history-electric-car

[2] Berner, R. A. The long-term carbon cycle, fossil fuels and atmospheric composition. *Nature*, 2003, 426(6964), 323.

[3] *Fossil*, https://www.energy.gov/science-innovation/energy-sources/fossil

[4] *Use of Energy in the United States Explained: Energy Use for Transportation*, U.S. Energy Information Administration, https://www.eia.gov/energyexplained/?page=us_energy_transportation

[5] Van Wee, B., Maat, K., & De Bont, C. Improving sustainability in urban areas: discussing the potential for transforming conventional car-based travel into electric mobility. *European Planning Studies*, *20*(1), 2012, 95-110.

[6] *Air Pollution*, National Institute of Environmental Health Sciences, https://www.niehs.nih.gov/health/topics/agents/air-pollution/index.cfm

[7] *Reducing Pollution with Electric Vehicles*, Office of Energy Efficiency & Renewable Energy, https://energy.gov/eere/electricvehicles/reducing-pollution-electric-vehicles

[8] Michalek, J. J., Chester, M., Jaramillo, P., Samaras, C., Shiau, C. S. N., & Lave, L. B. Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proceedings of the National Academy of Sciences*, 2011, 108(40), 16554-16558.

[9] Samaras, C., & Meisterling, K. Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy. *Environmental Science & Technology*, 2008, 42(9), 3170-6.

[10] *Air Quality and Climate Change Research*, U.S. Environmental Protection Agency, https://www.epa.gov/air-research/air-quality-and-climate-change-research

[11] *The Consequences of Climate Change*, Global Climate Change, https://climate.nasa.gov/effects/

[12] *Climate Change May Bring Big Ecosystem Changes*, Global Climate Change, https://climate.nasa.gov/news/645/climate-change-may-bring-big-ecosystem-changes/

[13] *U.S. Regular Gasoline Prices*, https://www.eia.gov/petroleum/gasdiesel/

[14] eGallon, Office of Energy Efficiency & Renewable Energy, https://www.energy.gov/sites/prod/files/2013/06/f1/eGallon-methodology-final.pdf

[15] O'Malley, S., Zuby, D., Moore, M., Paine, M., & Paine, D. Crashworthiness Testing of Electric and Hybrid Vehicles. In *24th International Technical Conference on the Enhanced Safety of Vehicles (ESV) National Highway Traffic Safety Administration* (No. 15-0318), 2015

[16] Monthly Plug-in Sales Scorecard, https://insideevs.com/monthly-plug-in-sales-scorecard/

[17] National Highway Traffic Safety Administration, https://www.nhtsa.gov/ratings

[18] Lu, L., Han, X., Li, J., Hua, J., & Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. *Journal of power sources*, *226*, 2013, 272-288.

[19] *Electric Vehicles: Tax Credits and Other Incentives*, Office of Energy Efficiency & Renewable Energy, https://energy.gov/eere/electricvehicles/electric-vehicles-tax-credits-and-other-incentives

[20] *Zero Emission Vehicle (ZEV) Program*, California Air Resources Board, https://www.arb.ca.gov/msprog/zevprog/zevprog.htm

[21] *Regulations for Emissions from Vehicles and Engines*, U.S. Environmental Protection Agency, https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-model-year-2017-and-later-light-duty-vehicle

[22] Steinhilber, S., Wells, P., & Thankappan, S., Socio-technical inertia: Understanding the barriers to electric vehicles. *Energy Policy*, 60, 2013, pp.531-539.

[23] Egbue, O., & Long, S. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy policy*, *48*, 2012, pp.717-729.

[24] Sovacool, B. K., & Hirsh, R. F. Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition. *Energy Policy*, *37*(3), 2009, pp.1095-1103.

[25] Gould, J., & Golob, T. F. Clean air forever? A longitudinal analysis of opinions about air pollution and electric vehicles. *Transportation Research Part D: Transport and Environment*, *3*(3), 1998, pp.157-169.

[26] Horberry, T., Stevens, A., & Regan, M. A. (Eds.) *Driver acceptance of new technology: Theory, measurement and optimisation*. Ashgate Publishing, Ltd, 2014

[27] Rezvani, Z., Jansson, J., & Bodin, J. Advances in consumer electric vehicle adoption research: A review and research agenda. *Transportation research part D: transport and environment*, *34*, 2015, pp.122-136.

[28] J. Neubauer, and E. Wood, The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility, *Journal of Power Sources 257*, 2014, 12-20.

[29] A. Hoen, and M.J. Koetse*, A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands*, Transportation Research Part A: Policy and Practice, 61, 2014, 199-21

[30] M. Tanaka, T. Ida, K. Murakami, and L. Friedman, Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan, *Transportation Research Part A: Policy and Practice* 70, 2014, 194-209.

[31] *2017 Battery Electric Cars Reported Range Comparison*, https://www.fleetcarma.com/2017-battery-electric-cars-reported-range-comparison/

[32] Wejnert, B. Integrating models of diffusion of innovations: A conceptual framework. *Annual review of sociology*, 2002, pp.297-326.

[33] Keith, D. R. Essays on the dynamics of alternative fuel vehicle adoption: insights from the market for hybrid-electric vehicles in the United States, PhD diss., Massachusetts Institute of Technology, 2012.

[34] Swan, J. A., & Newell, S. The role of professional associations in technology diffusion. *Organization studies*, *16*(5), 1995, pp.847-874.

[35] Dua, R., White, K., & Lindland, R. Understanding Adoption of Energy-Efficient Technologies: A Case Study of Battery Electric Vehicle Adoption in the U.S., *KAPSARC*, 2016, KS-1638-DP032A

[36] Carley, S., Krause, R. M., Lane, B. W., & Graham, J. D. Intent to purchase a plug-in electric vehicle: A survey of early impressions in large US cites. *Transportation Research Part D: Transport and Environment*, *18*, 2013, pp.39-45.

[37] Global EV Outlook 2016. Beyond one million electric cars. *International energy agency*, 2016

[38] Hayward, L., *Infographic: state of the electric vehicle market*, The fuse, 2015, http://energyfuse.org/infographic-state-of-the-electric-vehicle-market/

[39] Shepardson, D. and WOODALL B., *Electric vehicle sales fall far short of Obama goal*, January 2016, Reuters. http://www.reuters.com/article/us-autos-electric-obama-insight-idUSKCN0UY0F0

[40] *Feasibility and Implications of Electric Vehicle (EV) Deployment and Infrastructure Development*, FHWA-HEP-15-021, Chapter 3, http://www.fhwa.dot.gov/environment/climate_change/mitigation/publications/ev_deployment/es.cfm. Accessed January, 2015

[41] Rogers, E. M. *Diffusion of innovations*. Simon and Schuster, 2010

[42] Cahill, E. C., Davies, J., Turrentine, T., & Sperling, D. Zero-Emission Vehicles and Retail Innovation in the US Automotive Sector: The Consumer Purchase Experience and Dealer Engagement. In *Transportation Research Board 94th Annual Meeting* (No. 15-0753), 2015

[43] MaritzCX consumer satisfaction study 2011-2015, MaritzCX

[44] Cattaneo, M. Matching. In Neil J. Salkind (Ed.), Encyclopedia of Research Design. Thousand Oaks, CA: *SAGE Publications, Inc.*, 2010, pp. 759-762.

[45] Sekhon, J. S. Multivariate and propensity score matching software with automated balance optimization: the matching package for R. *Journal of Statistical Software, Forthcoming*, 2008

[46] Baltas, G., & Saridakis, C. An empirical investigation of the impact of behavioural and psychographic consumer characteristics on car preferences: An integrated model of car type choice. *Transportation Research Part A: Policy and Practice*, *54*, 2013, pp.92-110.

[47] Imbens, G. W. Matching methods in practice: Three examples. *Journal of Human Resources*, *50*(2), 2015, pp.373-419.

[48] Knittel, C. R., Jacobsen, M., Miller, D., Rapson, D., Soderbery, A., Sperling, D., & Wolak, F. Automobiles on Steroids: Product Attribute Trade-offs and. In *Technological Progress in the Automobile Sector, Working Paper 15162*, *National Bureau of Economic Research*, 2009

[49] MacKenzie, D., Zoepf, S., & Heywood, J. Determinants of US passenger car weight. *International Journal of Vehicle Design*, *65*(1), 2014, 73-93.

[50] Rubin, D. B. Using propensity scores to help design observational studies: application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*(3-4), 2001, 169-188.

[51] Mishra, G. S., Clewlow, R. R., Mokhtarian, P. L., & Widaman, K. F. The effect of carsharing on vehicle holdings and travel behavior: A propensity score and causal mediation analysis of the San Francisco Bay Area. *Research in Transportation Economics*, *52*, 2015, 46-55.

[52] Cao, X. J., Xu, Z., & Fan, Y. Exploring the connections among residential location, self-selection, and driving: Propensity score matching with multiple treatments. *Transportation research part A: policy and practice*, *44*(10), 2010, 797-805.

[53] Rephann, T., & Isserman, A. New highways as economic development tools: An evaluation using quasi-experimental matching methods. *Regional Science and Urban Economics*, *24*(6), 1994, 723-751

[54] Kvam, P. H., & Vidakovic, B. (2007). *Nonparametric statistics with applications to science and engineering* (Vol. 653). John Wiley & Sons, 2007

[55] Corder, G. W., & Foreman, D. I. nonparametric statistics for non-statisticians: a step-by-step approach, *Wiley InterScience*, Hoboken, N.J, 2009

[56] Kim, S., & Lee, W. Does McNemar's test compare the sensitivities and specificities of two diagnostic tests? *Statistical methods in medical research*, 0962280214541852, 2014

[57] Adedokun, O. A., & Burgess, W. D. Analysis of paired dichotomous data: A gentle introduction to the McNemar Test in SPSS. *Journal of Multi-Disciplinary Evaluation*, *8*(17), 2011, pp.125-131

[58] Tamhane, A. C., & Dunlop, D. D. *Statistics and data analysis: from elementary to intermediate* (Vol. 1), Prentice Hall, 2000

[59] Hidrue, M. K., Parsons, G. R., Kempton, W., & Gardner, M. P. Willingness to pay for electric vehicles and their attributes. *Resource and Energy Economics*, *33*(3), 2011, pp.686-705

[60] Sierzchula, W., Bakker, S., Maat, K., & van Wee, B. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. *Energy Policy*, *68*, 2014, pp.183-194.

[61] Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., ... & Daly, A. Hybrid choice models: progress and challenges. *Marketing Letters*, *13*(3), 2002, 163-175.

[62] E. J. Traut, T. C. Cherng, C. Hendrickson, & J. J. Michalek, US residential charging potential for electric vehicles. *Transportation Research Part D: Transport and Environment*, 2013, *25*, 139-145.

[63] J. Smart, and S. Schey, *Battery electric vehicle driving and charging behavior observed early in the EV project,* SAE Int. J. Altern. Powertrains 1.1, 2012, 27-33.

[64] C. Botsford, and A. Szczepanek, *Fast charging vs. slow charging: Pros and cons for the new age of electric vehicles,* In International Battery Hybrid Fuel Cell Electric Vehicle Symposium 2009.

[65] P. J. Fontaine, Shortening the path to energy independence: a policy agenda to commercialize battery–electric vehicles, *The Electricity Journal, 21*(6), 2008, 22-42.

[66] P. Morrissey, P. Weldon, and M. O'Mahony. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behavior, *Energy Policy*, 89, 2016, 257-270.

[67] J. Wishart, *Lessons Learned - DC Fast charge – Demand Charge Reduction*, The EV Project, Electric Transportation Engineering Corporation, 2012

[68] R.C. Larson, and A.R. Odoni, *Urban operations research*, ISBN 978-0975914632, Massachusetts, Dynamic Ideas, 2007

[69] F. Schneider, Frank, U. Thonemann, and D. Klabjan, *Optimization of Battery Charging and Purchasing at Electric Vehicle Battery Swap Stations*, Working Paper, 2013.

[70] The EV Project: *Characterize the demand and energy characteristics of direct current fast chargers*, http://www.avt.inl.gov/, June 2015

[71] California Energy Commission: Consideration for corridor direct current fast charging infrastructure in California, http://www.energy.ca.gov/

[72] Fuel Economy, https://www.fueleconomy.gov/, 2016

[73] D. L. Greene, Survey evidence on the importance of fuel availability to the choice of alternative fuels and vehicles. *Energy Studies Review*, 8.3, 1998.

[74] D. Chang, et al., *Financial Viability of Non-Residential Electric Vehicle Charging Stations*, Luskin Center for Innovation: Los Angeles, CA, 2012.

[75] Wiederer, and R.Philip, Policy options for electric vehicle charging infrastructure in C40 cities, Master Thesis, Harvard Kennedy School, 2010.

[76] EV adoption, fast charger operations, and project economics, https://queueingmodel.shinyapps.io/queueingapp/