ANALYSIS OF ELECTRIC VEHICLE PURCHASER SATISFACTION AND REJECTION REASONS

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ABSTRACT

This study uses a matched data set drawn from more than 1 million new vehicle post-purchase consumer satisfaction surveys to test for differences in satisfaction and reasons for vehicle choice and rejection between conventional internal combustion engine (ICE) vehicles and plug-in electric vehicles (PEVs). We use the Wilcoxon signed rank test and the McNemar and chi-squared tests to evaluate consumer satisfaction and reasons for rejecting considered vehicles, respectively. Results show that PEV purchasers and considerers are less satisfied with their overall purchase experience, but those who considered and rejected a PEV were less likely than those who considered and rejected an ICE to cite the dealer's attitude as the reason for rejection. Price and value were the most cited reasons and were similarly important for both groups. Reasons related to model availability and vehicle attributes were more often a concern for PEV considerers than ICE considerers. These results suggest that even with existing incentives, the limitations of the current technology (e.g. price and range) and variety of available vehicles are the most important challenges to market expansion.

Keywords: Electric vehicle, PEV, Customer satisfaction, Customer behavior, Consumer choice, Consumer rejection

INTRODUCTION AND BACKGROUND

Automakers are bringing an increasing number of plug-in electric vehicles (PEVs) to market, comprising both battery electric (BEVs) and plug-in hybrid electric vehicles (PHEVs). Even with substantial support from various government regulations and policies, sales volumes in the US continue to fall short of official goals (*1*), and modeled projections (*2*). Researchers, policy makers, and industry point to many barriers on the way to adoption of PEVs, including range anxiety, lack of charging infrastructure, high costs, and others. Numerous studies have tried to understand and address these barriers (*3, 4, 5, 6, 7, 8*).

In the last couple of years there have been noticeable improvements in battery technology, cost, and charging infrastructure availability (*9*). These improvements, and the resulting vehicle design changes may help to 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, and PEV annual sales grew from 2011 to 2014 (*10*). However, sales are still far behind President Obama's goal to have 1 million plug-in vehicles on the roads by 2015 (*11*).

Unfamiliarity with PEV technology is another key barrier for PEV adoption. As noted by Gould & Golob (*5*) "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 (*6, 7, 12, 13, 14*). 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 (*7*). Several studies recognize these characteristics among PEV adopters. Some studies indicate that being technophiles and having environmental concerns as PEV buyers' notable characteristics (*4, 15, 16*). Being highly educated and a previous owner of a hybrid car are others (*16*). Even among "technologically minded" individuals, the perceptions of PEVs vary with demographics such as gender, level of education, and age (*4*).

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 in order to broaden the PEV market from innovators to the early adopters who may be more sensitive to these rejection factors (*17*). 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 looked into 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 (*18*). 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 paper, 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 (*19*). 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.

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 (*21, 22*). 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 (*20*). 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 (*23*). Matching has been widely applied to problems such as measuring changes in vehicle technology (*24,25*), the effects of smoking (*26*), the effects of carsharing (*27*) and residential location choice (*28*) on travel demand, and the economic impacts of new roads (*29*), 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 (*26*). 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 (*20*). 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 (*30*). The Wilcoxon signed rank test is used to test whether the medians for two paired samples are the same or not (*30, 31*) 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 (*23, 32, 33*). 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. In order 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 (*34*). 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 (*19*)

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

RESULTS

Matching Result

Figure 1 contains the summary statistics of the four chosen characteristics of individuals for unmatched samples of ICE purchasers and PEV purchasers. We also used gender for matching. Before matching, ICE purchasers were 31% females, 48% males and 21% not answered; PEV purchasers were 22% females, 57% males and 21% not answered. 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.

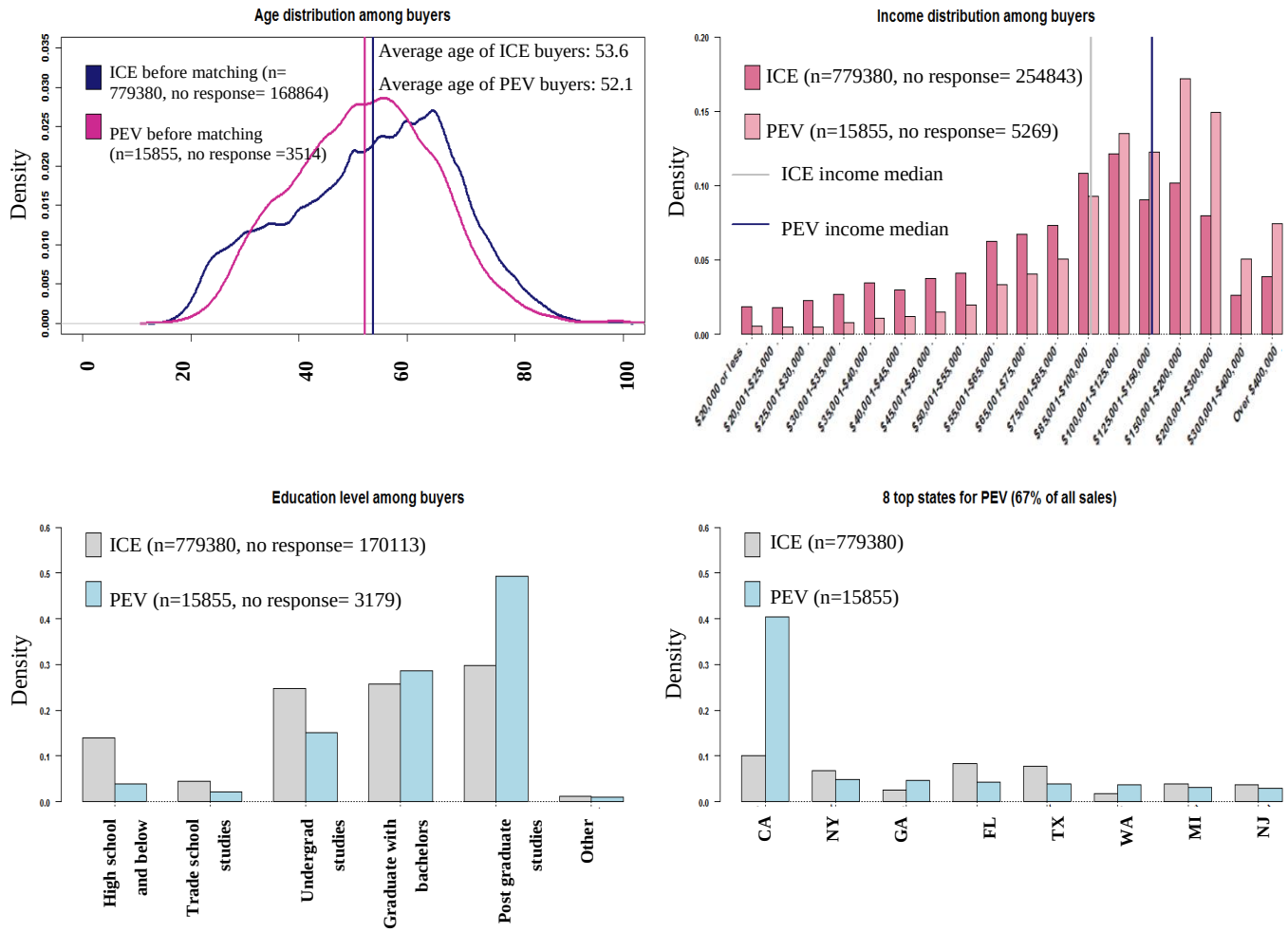

FIGURE 1 Summary of demographics before matching

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 Hybrid	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.

Consumer Satisfaction with Purchase Experience

Figure 2 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 = 3.675×10^{-6}), indicating that we should reject the null hypothesis of no difference in satisfaction between similar PEV and ICE purchasers.

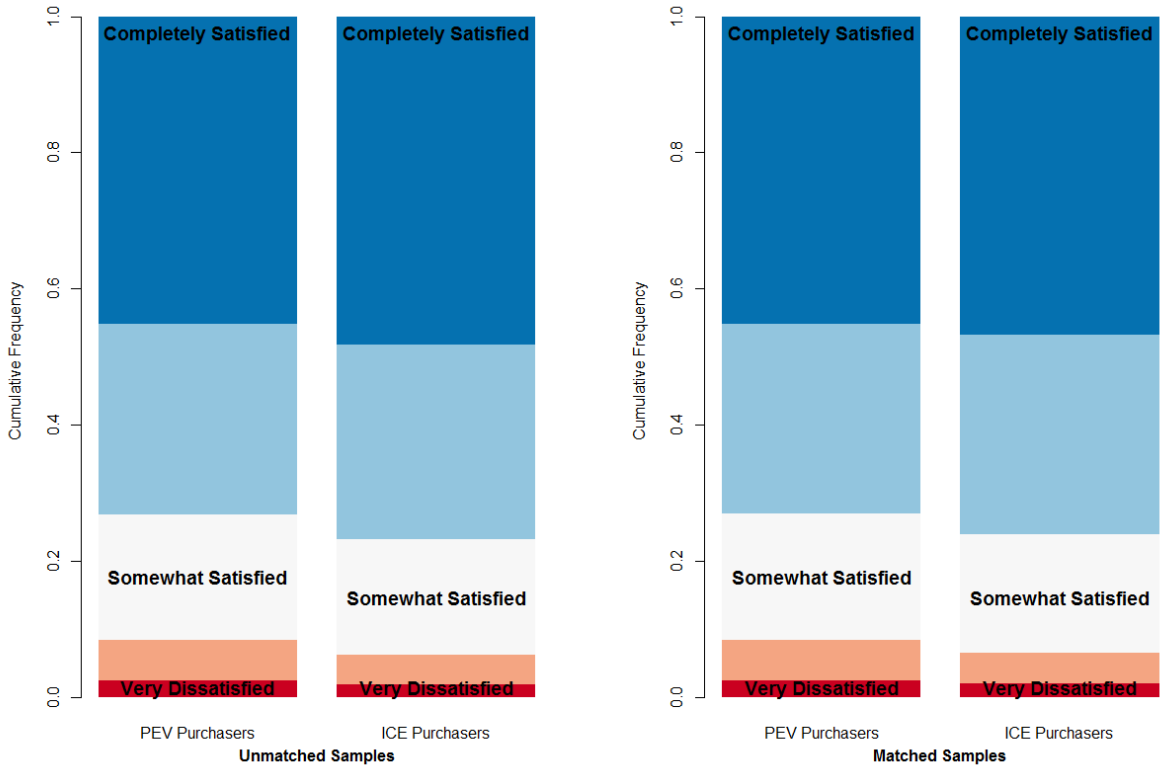

FIGURE 2 Cumulative frequency of levels of satisfaction for PEV purchasers and ICE purchasers

Figure 3 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.

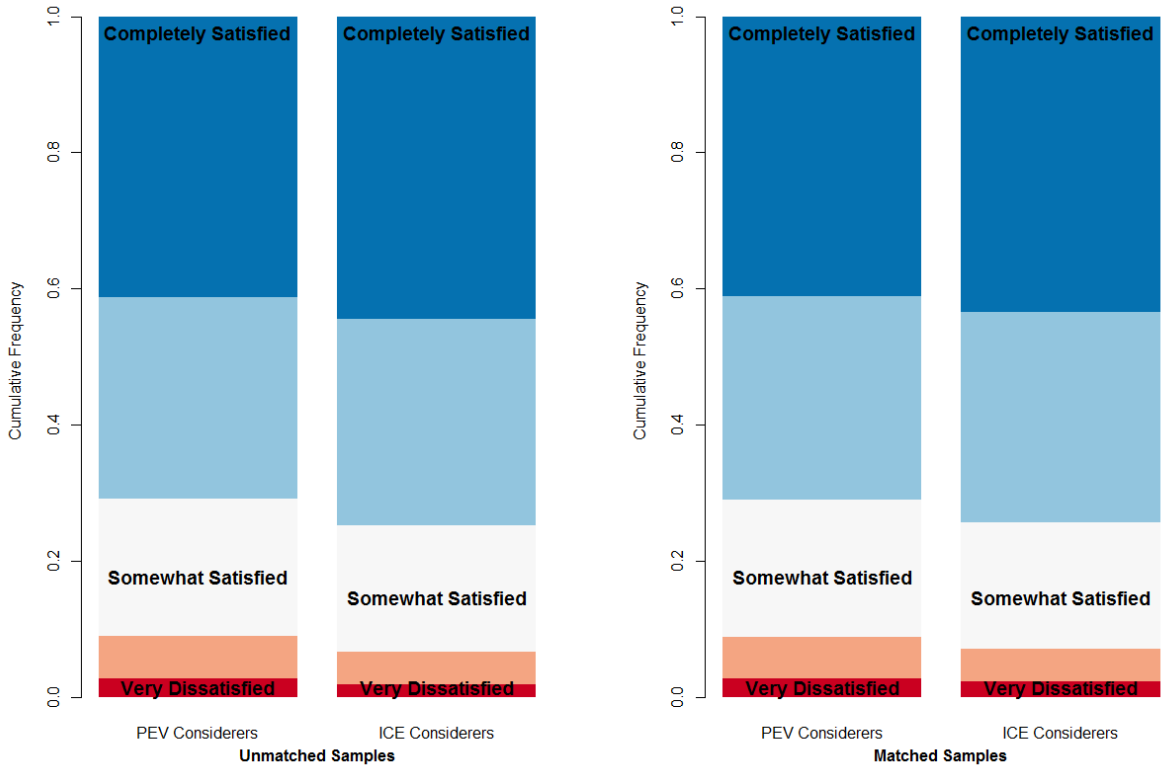

FIGURE 3 Cumulative frequency of levels of satisfaction for PEV considerers and ICE considerers

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

	McNemar Result	Chi-squared
Reasons	average *p*-value (150 repetitions)	*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 4 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 as a result 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 4 and 5 we find out which reasons are important for each group in general based on frequency of citation.

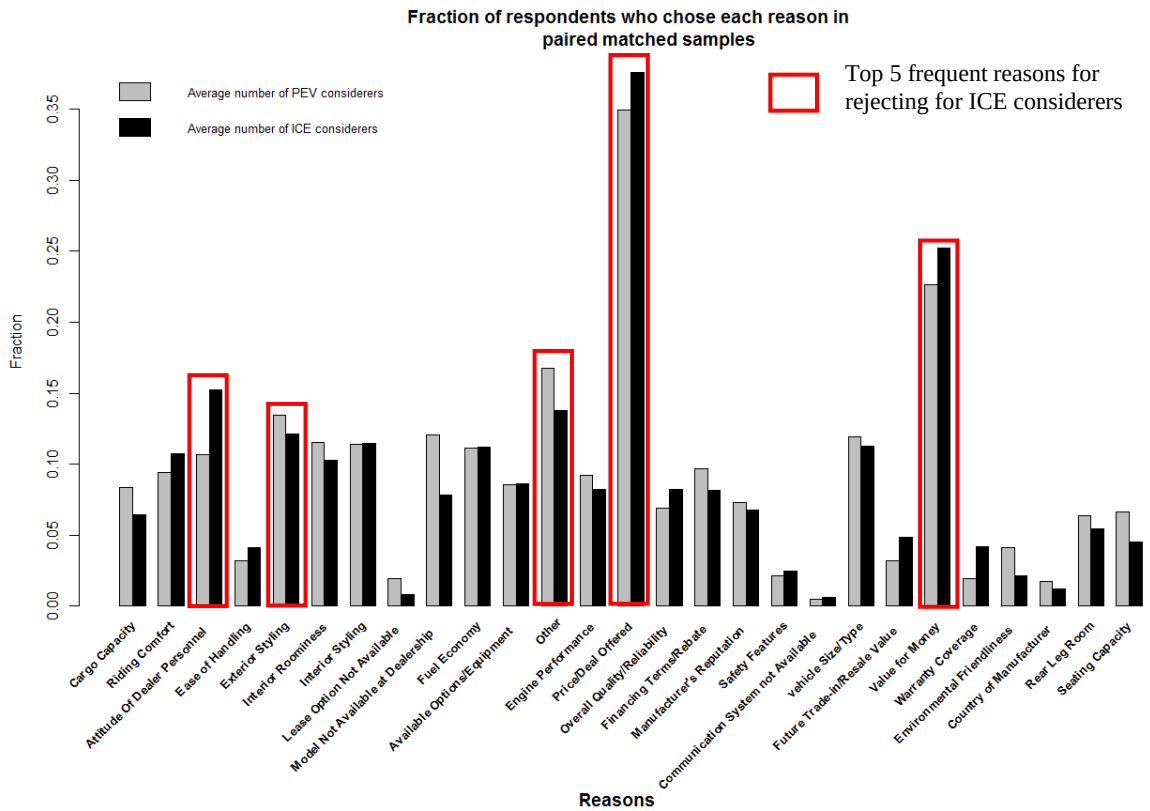

FIGURE 4 Fraction of respondents who chose each reason in paired matched samples (1 ICE considerer matched to each PEV considerer)

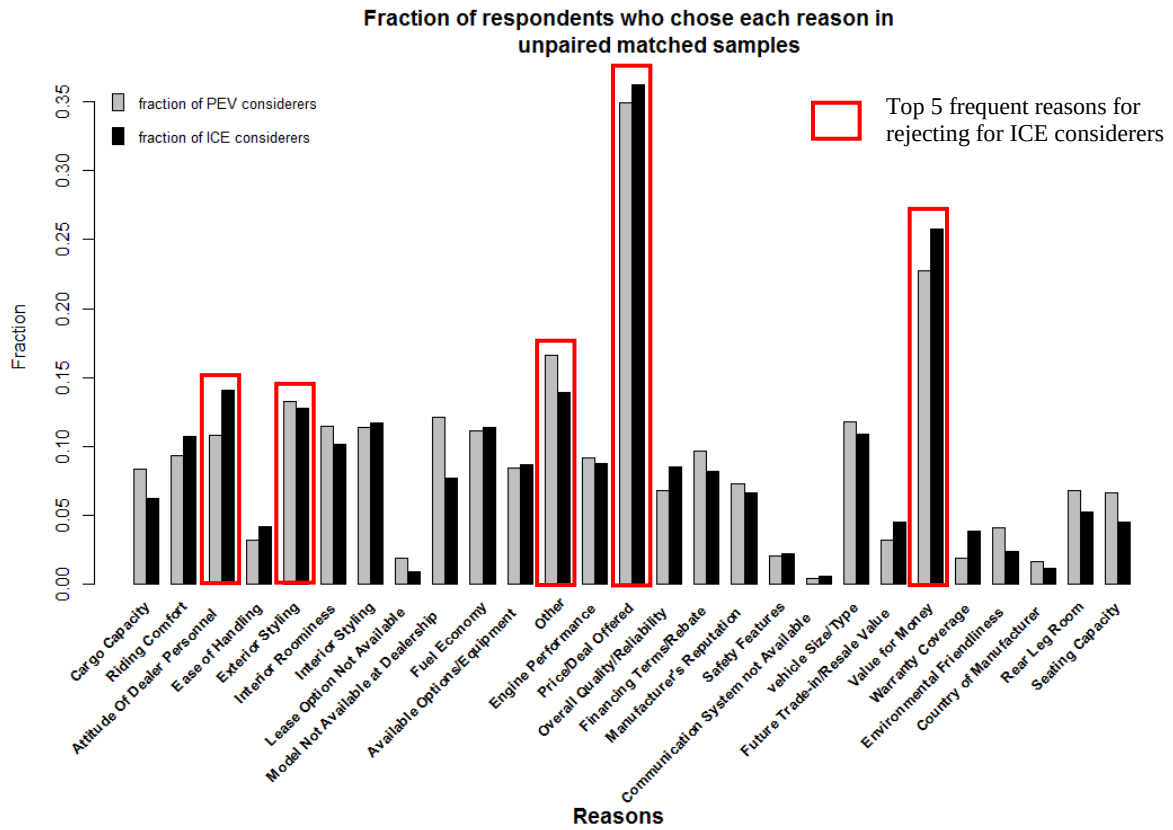

FIGURE 5 Fraction of respondents who chose each reason for unpaired matched samples (multiple ICE considerers matched to each PEV considerer)

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.

DISCUSSION AND CONCLUSIONS

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 (*20*). 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 2 and figure 3 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 1 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 (*35,36*).

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 4 and figure 5, 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 (*35*) 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 (*18*), 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.

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 (*37*) 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 costumers, 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.

References

1. 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

2. *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

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

4. 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.

5. 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.

6. 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.

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

8. 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.

9. Global EV Outlook 2016. Beyond one million electric cars. *International energy agency*, 2016

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

11. FACT SHEET: President Obama's Plan to Make the U.S. the First Country to Put 1 Million Advanced Technology Vehicles on the Road, the White House, Office of the Press Secretary, Accessed January 25, 2011

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

13. 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.

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

15. 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

16. 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.

17. Rogers, E. M. *Diffusion of innovations*. Simon and Schuster, 2010

18. 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

19. MaritzCX consumer satisfaction study 2011-2015, MaritzCX

20. 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.

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

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

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

24. 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

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

26. 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.

27. 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.

28. 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.

29. 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

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

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

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

33. 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

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

35. 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

36. 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.

37. 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.