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Characterizing Plug-in Hybrid Electric Vehicle Consumers Who Found the U.S. Federal Tax Credit Extremely Important in Enabling Their Purchase

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Summary

The U.S. federal tax credit (FTC) of up to $7,500 for the adoption of plug-in electric vehicles (EVs) is being phased out. To better understand the role the FTC has played, this research analyses survey responses from 3,452 recipients of California's state-wide EV rebate (CVRP) who purchased a plug-in hybrid EV (PHEV) from November 2016 through December 2018. This work uses logistic regression to identify qualities (demographic, household, and transaction characteristics; motivations; and experience) associated with consumers rating the FTC "Extremely Important" to making their PHEV purchase possible. Findings both inform retrospective assessments and calibrate expectations about future market impacts.

Keywords: electric vehicle (EV), consumers, federal, incentive, policy

1 Introduction

Problem. The U.S. federal tax credit (FTC) for the adoption of plug-in electric vehicles (EVs) provides up to $7,500 to reduce the costs of acquisition—a potentially powerful enabler. A phase-down process is triggered once an automaker sells 200,000 EVs, initially leading to the halving of the FTC, followed by a subsequent halving, and ultimately to the elimination of the credit for all vehicles that automaker sells [1]. FTC phase out (elimination) occurred for Tesla vehicles at the end of 2019 and is occurring for GM vehicles at the end of March 2020. Who has found the FTC most influential? What will the effects of FTC phase-out be? Assessment of who the FTC has influenced can calibrate expectations and inform discussions about optimal policies moving forward.

Previous Related Work by the Authors. A 2017 report summarized the responses to the CVRP Consumer Survey, 2013–15 Edition—which includes ratings of FTC importance [2]. A 2019 presentation expands that perspective somewhat with slides summarizing more recent data from California and from three other state-wide EV programs (Massachusetts, Connecticut, and New York) [3]. Related peer-reviewed analysis of the influence of EV incentives includes (but is not limited to) characterization of consumers who were highly influenced by state rebates to purchase/lease EVs, or "*Rebate Essential*" consumers [4,5]. Like the work presented here, those papers analysed EV market segments using logistic regression.

Overview of Contributions. This research used descriptive statistics and logistic regression methods to identify characteristics associated with rating the FTC "Extremely Important" to making EV acquisition possible. It used recent data from rebated California consumers who purchased a plug-in hybrid electric vehicle (PHEV) from November 2016 through December 2018 (n = 3,452). Consumers of battery electric vehicles (BEVs) will be examined separately and differences will be highlighted at EVS33. Like previous work, this research utilized binary logistic regression to identify qualities—demographic, household, and regional characteristics; purchase motivations; and vehicle-transaction details—that significantly increase the odds of rating the FTC "Extremely Important." Significant and notable nonsignificant findings are discussed, compared to descriptive measures, and rank-ordered by importance to inform assessments of past and future FTC impacts.

2 Data & Representativeness

The California Clean Vehicle Rebate Project (CVRP) provides cash rebates to consumers for the purchase or lease of clean vehicles. CVRP administers a Consumer Survey for rebated nonfleet individuals. This research utilized data from consumers who purchased a PHEV from November 2016 through December 2018 and had been approved for a rebate as of April 5, 2019 (Table 1). The end of this time range represents the most-recent data available at the time of analysis. The start date of this time period coincides with a major program change in CVRP that introduced income-based criteria to the program, including a cap on eligible consumer household income and an Increased Rebate for lower-income applicants [6]. This start date was utilized for the data to represent a cohesive group and because the overall objective is to inform analysis of changes to the current program. In brief, the data constitute the most recent "current-program" era available.

Table 1: California CVRP Consumer Survey Data Utilized (Rebated Private Individuals)

Survey Response Dates	11/15/2016–04/07/2019	Purchase/Lease Dates	11/01/2016–12/31/2018
Plug-in EV Portion of Program Participant Population	N = 137,715* • PHEVs = 48,166 • BEVs = 85,245 • FCEVs = 4,304	Weighting Method Representative Dimensions	Raking Vehicle tech. type, model, purchase vs. lease, residence county
Plug-in EV Responses in Dataset	n = 27,508* • PHEVs = 9,432 • BEVs = 17,048 • FCEVs = 1,028	Program as % of Plug-in EV Market	~49% [7]

* Note: n was calculated as of 4/7/2019 and N as of 3/2/2020. These are technically not directly comparable because ~4,400 applicants who purchased/leased EVs in 2018 were added to the program in the interim due to an 18-month application window.

Using application information provided by all participants, response weights were computed to make the data more representative of all program participants (Table 1). Similar weights are regularly used elsewhere [2,8–10]. For purposes of understanding the past and future impacts of the FTC on CVRP, program participants are the population of direct interest. For those with broader interests, CVRP is not necessarily representative. However, CVRP participants currently constitute about half of the California plug-in EV market (Table 1).

3 Methodology

Overview. The objective was to characterize consumers who might not have been able to adopt their EV without the FTC. The descriptive analysis used weighted response frequencies to produce pertinent demographic metrics for consumers with Extreme FTC Importance and provided context for those metrics with appropriate baselines of comparison. The modelling approach was binary logistic regression to identify characteristics that increase the odds of having Extreme FTC Importance. Results of a Full Model were examined for significance and notable nonsignificance. Significant Parsimonious Model results were ranked-ordered in importance and discussed.

Outcome Variable. The outcome variable was constructed from the survey question, "How important were each of the following factors in making it possible for you to acquire your clean vehicle? [Federal tax incentives]." Consumers who responded, "Extremely Important" constitute the "*FTC Extreme"* segment (Figure 1). The group of *FTC Extremes* is the closest available proxy for those consumers that would not have acquired their EV without the FTC, or "*FTC Essentials*." Indeed, in research characterizing "*Rebate Essentials"* [4,5], some similarities were found between those rating the state rebate "Extremely Important" and those who answered a counterfactual question stating they would not have purchased or leased their vehicle without the state rebate.

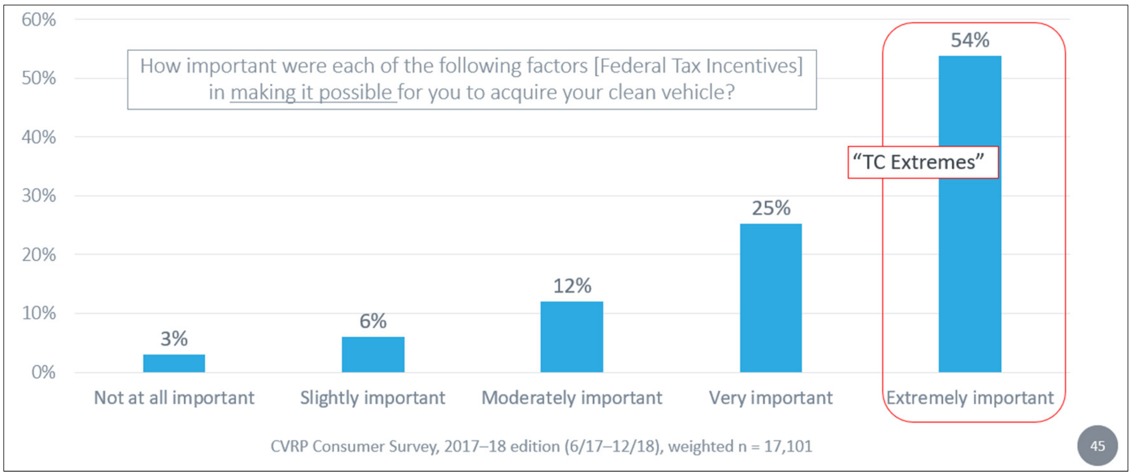

Figure 1: The Importance of the Federal Tax Credit in Enabling the EV Acquisition of CVRP Participants (Source:[3])

Respondents who selected, "Not at all important," "Slightly important," or "Moderately important" were grouped to form the non-extreme status. Because the *FTC Extreme* group is sufficiently large—generally constituting over half of the responses (Figure 1) and growing [3]—and to remove ambiguity from the binary contrast between *FTC Extremes* and those *not* highly influenced, consumers responding "Very Important" and "Not Applicable" were removed from the analytical dataset. Ordinal logistic regression was also considered but rejected due to concerns about assumption violations. Lessees were also removed because leasing companies can claim the FTC to provide lower lease rates, potentially clouding lessee awareness and understanding of the FTC and making their rating of FTC importance inconsistent and/or difficult to interpret.

General Data Preparation. Weighted data were used for the descriptive analysis to better represent the rebate population characterized, but unweighted data were used for the logistic regressions to reduce standard errors and bias, and to increase consistency [11]. Cases were removed that lacked an FTC importance response.

Predictor (Explanatory) Variable Preparation. The predictor variables include survey responses and application details characterizing the consumer, household, vehicle, and transaction. Available variables were evaluated for theoretical relevance and/or serviceability as program or policy levers. Not all predictor variables should be interpreted in the same way, as some are strictly explanatory in nature; causality is not analysed here. Rather, the predictor variables are used in their typical general sense, to predict the odds of a consumer being an *FTC Extreme*. Some variable bins were combined to ensure adequate cell size [12] (vehicle make, previous EVs owned, people in household, age, education, tax-filing status, most important motivating factor, and region). A very small number of respondents aged 16–20 were also dropped from the dataset. Some variables are ordinal binned values representing underlying continuous metrics (e.g., income, importance of a factor to the decision to adopt, etc.). Alternative variable data types (i.e., continuous vs. categorical) were evaluated by regressing the variables against the outcome variable. If a data type had a better fit, it was selected [13] (e.g., the number of licensed drivers in the household was treated as continuous). Income was binned to make steps sizes equivalent (excepting the open-ended highest bin). Purchase price was binned due to pre-modelling concerns about *FTC*

Extreme Importance having a nonlinear response to it. The race/ethnicity question was transformed from "select all that apply" into the following categories: selected solely White/Caucasian, selected solely East Asian or South Asian, and other selections (including multiple selections). Some variable responses were re-binned/classified or dropped and imputed to form fewer categories (gender, solar). For example, responses to questions about solar installation at home were re-binned/classified to collect "no" responses into a single category, including: "No, but I am planning to install solar panels within the next year," "No, and I have no plans to install solar panels," and "No, I am unable to install solar panels." When possible, write-in responses were mapped to the appropriate response category using a regex-based search of write-in responses (e.g., where the response started with the word "no" followed a space or punctuation). When not possible to sort or reclassify, responses were treated as missing. Included variables are summarized in the results section in Table 3.

Missing Data. Table 3 also shows the proportions of missing data. The highest proportion occurs for household income, but the missingness rate (12%) is less than rates achieved in other surveys [14]. Racial/ethnic identity had the next-highest non-response rate (10%). For the other variables displayed, rates of missingness were 4.1% or less. Missing data were addressed in two stages: First, listwise deletion was applied to variables with values missing for less than 1% of cases, checking that the total loss to sample size was less than 5%. Then, multiple imputation was applied, primarily motivated by the income variable for which missingness is not assumed to be missing completely at random. In this case, 15 imputed datasets were produced to generate variability [15,16].

Final Analytical Dataset. After trimming out leases (41% of 9,432 PHEV responses), deleting cases, and imputing missing values, the sample was reduced to a final analytical sample size of n = 3,452.

Full Model Specification. This PHEV-purchaser dataset was used to produce a "Full Model" to explore the directionality and (non)significance of a comprehensive set of controlling and explanatory variables. A binary logistic regression was fit using all predictor variables listed in Table 3 for each of the 15 datasets produced in the multiple imputation procedure described previously. The results were pooled using Rubin's rules via the MICE library [16,17]. Scatter plots of continuous predictors vs. the fitted logit values were examined for linearity [18]. Continuous variables of concern were examined to see if categorical treatment would address nonlinearity issues. In addition to binning purchase price, purchase month-year was transformed into a categorical year variable and this treatment was confirmed as acceptable. The initial Full Model was also tested for outliers with a standardized residual distance greater than three [18]. No such observations were observed. The Full Model was then re-run and the new results were pooled. Using Wald tests, joint significance of variables with categorical responses was used to verify significance of individual category coefficients. Significant individual categories in each of the region, previous EV ownership, tax-filing-status, and HOV-access-importance variables were not labelled significant due to lack of variable joint significance (but the latter two became jointly significant in the Parsimonious Model). The results of the final Full Model are also displayed in Table 3.

Parsimonious Model Specification. The Full Model was then reduced to a "Parsimonious Model" to provide a succinct set of the most meaningful predictors. Variables with variance inflation factors greater than 10 were considered for exclusion [12]. No such collinearity concerns were observed. Overall, model-reduction steps were:

1. Remove variables determined to be problematic due to concerns about covariance with other variables (CVRP rebate type; the importance ratings of saving money overall and charging on the way to non-work/-home destinations; and the overall most important motivating factor), and/or due to conceptual overlap with the outcome variable (CVRP rebate type, the importance of saving money overall, and *Rebate Essential*).
2. Produce a reduced interim model with problematic and related predictors removed.
3. Perform backward stepwise selection (Akaike information criterion) to nominate predictors for deletion. Drop predictors consistently nominated for deletion across all 15 datasets to produce a further-reduced model.
4. Check variables that were not consistently dropped by the stepwise selection algorithm for significance. Drop those not significant and re-specify another reduced model.
5. Drop remaining insignificant predictors to produce a Parsimonious Model with only significant predictors, verifying joint significance.

Dominance Ranking. To facilitate prioritization of predictors, a dominance analysis was performed [19]. Dominance analysis measures the impact of removing a predictor from the model. Here, the Average Contribution, a measure of the average change in pseudo-R^2 [20], was produced for each of the 15 versions of the Parsimonious Model. These 15 Average Contribution values were in turn averaged and rank-ordered.

4 Results & Discussion

4.1 Descriptive Results & Discussion

Building on previous work [2,3], Table 2 characterizes the *FTC Extremes* **segment**. It also provides an illustrative comparison with the new-car buying **market** as a whole. For example, it is estimated that the percentage of consumers 50 or more years old is 51% for both the *FTC Extreme* segment and new-vehicle buyers as a whole. However, on most dimensions, *FTC Extreme* PHEV consumers still appear substantially different than mainstream new-vehicle buyers. In this sense, compared to analysis of other strategic market segments, *FTC Extremes* may more closely resemble *Rebate Essentials* (who would not have purchased/leased their EV without the state rebate) than *EV Converts* (who had low initial interest in EVs). The latter group tends to more closely resemble new-car buyers overall than either of the other two groups [21]).

Table 2 Summary of *FTC Extreme* Segment Characteristics

	FTC Extremely Important to PHEV Purchase (weighted n = 2,213)	**CA New-Vehicle Buyers** MYs 2016–17 (2017 NHTS CA add-on [22]*)
Selected solely White/Caucasian	51%^	51%
≥ 50 Years Old	50%^	46%
≥ Bachelor's Degree in HH	82%^	58%*
Own Residence	81%	63%
≥ $100k HH Income	67%^	56%
Selected Male	70%	50%

"Prefer not to answer," "I don't know," and similar responses are excluded.

* NHTS is weighted to represent the population, not the new-vehicle subset. New-vehicle buyers identified based on a within-100-mile match between odometer and miles driven while owned. NHTS data characterize individual educational attainment, whereas other data characterize highest household attainment.

^ Significant difference ($p < 0.05$) between *PHEV FTC Extremes* and PHEV consumers *without* extreme FTC importance.

Testing descriptive statistics for significant differences between respondents with and without extreme FTC importance (indicated in Table 2 by carets on percentages in the *FTC Extreme* column) suggests that logistic regression might show a significant relationship between FTC Extreme Importance and ethnicity/race, age, education, and income.

4.2 Logistic Regression Modelling Results

Expressed as odds ratios (OR), the results in Table 3 show the multiplicative change in the odds of being an *FTC Extreme* if the predictor variable of interest increases by one unit, holding all other predictor variables constant. Odds ratios greater than one demonstrate a positive association between the predictor variable and the outcome variable, while odds ratios less than one show a negative association. For example, holding all other variables constant, if identification as female has an odds ratio of 0.80, it is associated with a 20% decrease in the odds of being an *FTC Extreme*. Odds ratios should not be compared across predictor variables: a one-unit change in the number of cars in the household (one car) is not directly comparable to a one-unit change in purchase quarter (three months). Significance is tested to the 95% level ($p < 0.05$) and indicated by an asterisk and cell shading. Green shading is used for a variable with positive association with *FTC Extreme* status (OR > 1) and red for negative association (OR < 1). Additionally, several instances of variables with $p \leq 0.10$ have no asterisk but are lightly shaded to highlight "borderline" candidates for more parsimonious or alternative model specifications.

Table 3: PHEV Variables and Model Results

Variable Description	Example Values	Missing	Full Model Odds Ratio	Pars. Model Odds Ratio	Dom. Rank
(Intercept)			0.001*	0.005*	
Demographic					
Age 30–39 (vs. 20–29)	1=true; 0=false	2.1%	1.50		
Age 40–49 (vs. 20–29)	1=true; 0=false	2.1%	1.29		
Age 50–59 (vs. 20–29)	1=true; 0=false	2.1%	1.28		
Age 60–69 (vs. 20–29)	1=true; 0=false	2.1%	1.13		
Age 70+ (vs. 20–29)	1=true; 0=false	2.1%	0.86		
Female (vs. male)	1=true; 0=false	2.9%	0.89	0.80*	13
Asian (vs. white)	1=true; 0=false	9.8%	1.03		
Not Asian or white (vs. white)	1=true; 0=false	9.8%	0.83		
Some college (vs. high school or less)	1=true; 0=false	2.1%	1.62	1.95*	10
Associates degree (vs. high school or less)	1=true; 0=false	2.1%	1.87	2.07*	
Bachelor's degree (vs. high school or less)	1=true; 0=false	2.1%	1.88*	2.58*	
Postgrad. degree (vs. high school or less)	1=true; 0=false	2.1%	2.07*	2.61*	
Married filing jointly (vs. single)	1=true; 0=false	3.6%	1.07	0.97	12
Married filing separately (vs. single)	1=true; 0=false	3.6%	0.38	0.40*	
Widower or head of household (vs. single)	1=true; 0=false	3.6%	1.08	1.13	
Household					
\$50k–\$100k (vs. < \$50k)	1=true; 0=false	12.0%	1.43		
\$100k–\$150k (vs. < \$50k)	1=true; 0=false	12.0%	1.19		
\$150k–\$200k (vs. < \$50k)	1=true; 0=false	12.0%	1.34		
\$200k–\$250k (vs. < \$50k)	1=true; 0=false	12.0%	1.14		
\$250k–\$300k (vs. < \$50k)	1=true; 0=false	12.0%	1.66		
\$300k or more (vs. < \$50k)	1=true; 0=false	12.0%	1.32		
Two people in household (vs. 1)	1=true; 0=false	1.6%	0.77		
Three people in household (vs. 1)	1=true; 0=false	1.6%	0.83		
Four people in household (vs. 1)	1=true; 0=false	1.6%	0.62		
Five or more people in household (vs. 1)	1=true; 0=false	1.6%	0.55		
Number of drivers in household	1=one;…9=nine +	1.7%	1.09		
Number of vehicles in household	1=one;…4=four +	1.2%	1.03		
Additional household vehicle (vs. replaced)	1=true; 0=false	0.3%	1.13		
Previously owned 1 EV (vs. have not)	1=true; 0=false	0.2%	0.98		
Previously owned 2+ EVs (vs. have not)	1=true; 0=false	0.2%	1.74		
Rent home (vs. own)	1=true; 0=false	3.4%	0.94		
Multi-unit dwelling (vs. single-family)	1=true; 0=false	1.5%	1.11		
Attached house (vs. single-family)	1=true; 0=false	1.5%	1.05		
Other housing type (vs. single-family)	1=true; 0=false	1.5%	0.51		
Solar installed prior to EV (vs. no solar)	1=true; 0=false	4.1%	1.02		
Solar installed with EV (vs. no solar)	1=true; 0=false	4.1%	0.93		
Regional					
Central (vs. Bay Area)	1=true; 0=false	0.0%	0.62		
Central Coast (vs. Bay Area)	1=true; 0=false	0.0%	1.03		
Far South (vs. Bay Area)	1=true; 0=false	0.0%	0.89		
North (vs. Bay Area)	1=true; 0=false	0.0%	0.86		
South (vs. Bay Area)	1=true; 0=false	0.0%	1.01		

Motivational					
Enviro impact: Extremely import (vs. not)	1=true; 0=false	0.6%	1.37		
Enviro impact: Very important (vs. not)	1=true; 0=false	0.6%	1.16		
Enviro impact: Mod. import (vs. not)	1=true; 0=false	0.6%	1.06		
Enviro impact: Somewhat import (vs. not)	1=true; 0=false	0.6%	1.13		
Energy indpndnce extrm imprt (vs. < extrm)	1=true; 0=false	0.9%	1.35*	1.30*	8
Chargng convnience: Extrm import (vs. not)	1=true; 0=false	0.9%	1.32		
Charging conv.: Very important (vs. not)	1=true; 0=false	0.9%	1.30		
Charging conv.: Moderately import (vs. not)	1=true; 0=false	0.9%	0.99		
Charging conv.: Somewhat import (vs. not)	1=true; 0=false	0.9%	0.73		
Chrgng avail–home: Extrmly imprt (vs. not)	1=true; 0=false	0.7%	1.71*	1.54*	6
Charging avail–home: Very import (vs. not)	1=true; 0=false	0.7%	0.94	0.92	
Charging avail–home: Mod. import (vs. not)	1=true; 0=false	0.7%	0.86	0.82	
Chrgng avail–home: Slightly imprt (vs. not)	1=true; 0=false	0.7%	0.72	0.66*	
Charging avail–work: Extr imprt (vs. not)	1=true; 0=false	1.8%	1.94*	2.65*	2
Charging avail–work: Very import (vs. not)	1=true; 0=false	1.8%	1.55*	1.79*	
Charging avail–work: Mod. import (vs. not)	1=true; 0=false	1.8%	0.99	1.19	
Chrgng avail–work: Slightly imprt (vs. not)	1=true; 0=false	1.8%	1.00	1.26	
Charging avail–other: Extr imprt (vs. not)	1=true; 0=false	1.3%	1.66	2.23*	4
Charging avail–other: Very import (vs. not)	1=true; 0=false	1.3%	1.20	1.78*	
Charging avail–other: Mod. import (vs. not)	1=true; 0=false	1.3%	1.00	1.14	
Chrgng avail–other: Slightly imprt (vs. not)	1=true; 0=false	1.3%	1.00	0.97	
Charging avail–on way: Extr imprt (vs. not)	1=true; 0=false	1.9%	1.13		
Chrging avail– on way: Very imprt (vs. not)	1=true; 0=false	1.9%	1.44		
Chrging avail–on way: Mod. imprt (vs. not)	1=true; 0=false	1.9%	0.76		
Chrgng avail–on way: Slight imprt (vs. not)	1=true; 0=false	1.9%	1.06		
HOV access: Extremely important (vs. not)	1=true; 0=false	1.0%	1.42	2.29*	3
HOV access: Very important (vs. not)	1=true; 0=false	1.0%	1.48	1.85*	
HOV access: Moderately import (vs. not)	1=true; 0=false	1.0%	1.08	1.36*	
HOV access: Somewhat important (vs. not)	1=true; 0=false	1.0%	0.94	1.05	
Saving $ on fuel: Extremely import (vs. not)	1=true; 0=false	1.6%	3.07*	5.71*	1
Saving $ on fuel: Very important (vs. not)	1=true; 0=false	1.6%	2.43	3.22*	
Saving $ on fuel: Mod. important (vs. not)	1=true; 0=false	1.6%	2.14	2.00	
Saving $ on fuel: Somewht import (vs. not)	1=true; 0=false	1.6%	2.17	1.79	
Saving $ overall: Extremely import (vs. not)	1=true; 0=false	1.3%	2.85*	removed	
Saving $ overall: Very important (vs. not)	1=true; 0=false	1.3%	1.96*	removed	
Saving $ overall: Mod. important (vs. not)	1=true; 0=false	1.3%	1.39	removed	
Saving $ overall: Somewht import (vs. not)	1=true; 0=false	1.3%	1.21	removed	
Desire for new tech: Extr import (vs. not)	1=true; 0=false	0.9%	1.21		
Desire for new tech: Very import (vs. not)	1=true; 0=false	0.9%	1.03		
Desire for new tech: Mod. import (vs. not)	1=true; 0=false	0.9%	0.95		
New tech: Somewhat important (vs. not)	1=true; 0=false	0.9%	0.90		
Vehicle perform: Extrmly imprtnt (vs. not)	1=true; 0=false	0.8%	0.96		
Vehicle perfrmnce: Very important (vs. not)	1=true; 0=false	0.8%	0.81		
Vehicle perfrmnce: Mod. important (vs. not)	1=true; 0=false	0.8%	0.71		
Vehicle perfrmnce: Somewht imprt (vs. not)	1=true; 0=false	0.8%	0.88		
Most imprt factor: Enviro impact (vs. other)	1=true; 0=false	0.2%	0.63*	removed	
Most imprt fctr: Saving $ on fuel (vs. other)	1=true; 0=false	0.2%	0.87	removed	
Most imprt fctr: Saving $ overall (vs. other)	1=true; 0=false	0.2%	1.52*	removed	
Transactional					
Model's max. tax credit (per $1,000)	4–8 (rounded to 1,000s)	0.0%	1.89*	1.73*	5
Initial knowledge/interest in an EV	0=no knwl;…5=only int.	0.1%	0.99		
Rebate Essential (vs. not *Rebate Essential*)	1=true; 0=false	0.8%	11.26*	removed	
Increased Rebate (vs. Standard Rebate)	1=true; 0=false	0.0%	0.49*	removed	
Purchase price $30k–$40k (vs. < $30k)	1=true; 0=false	0.0%	0.78	0.72*	11

Purchase price $40k–$50k (vs. < $30k)	1=true; 0=false	0.0%	0.53*	0.52*	
Purchase price > $50k (vs. < $30k)	1=true; 0=false	0.0%	0.56	0.53	
Purchase year 2017 (vs. 2016)	1=true; 0=false	0.0%	1.03		
Purchase year 2018 (vs. 2016)	1=true; 0=false	0.0%	0.89		
Purchase quarter	1–4	0.0%	1.15*	1.16*	9
Chevrolet (vs. other makes)	1=true; 0=false	0.0%	0.29*	0.42*	7
Honda (vs. other makes)	1=true; 0=false	0.0%	0.40*	0.48*	
Toyota (vs. other makes)	1=true; 0=false	0.0%	0.63*	0.81	

removed = Variable would have been significant in Parsimonious Model but removed due to concerns described in section 3.

Nonsignificance should not be taken as definitive proof of the unimportance of a predictor, but rather as a failure to detect any significance, if any exists. Regardless, *PHEV FTC Extremes* do not appear to be distinguished by race/ethnicity, unlike *PHEV Rebate Essentials* [5] but like *PHEV EV Converts*" [21]. On the other hand, higher educational attainment appears to play a role, like *Rebate Essentials* and unlike *EV Converts.*

Interestingly, household income does not predict the odds of being in any of the three PHEV segments. Perhaps this indicates that CVRP's income cap has sufficiently blunted any impact differences in income might otherwise have in differentiating incentive influence amongst program participants. As with *Rebate Essentiality,* only the large step-function difference in income represented by receiving CVRP's Increased Rebate for households under 300% of the federal poverty level (or not), helps predict FTC importance. Opposite to *Rebate Essentiality,* being below that threshold actually decreases the importance of the FTC incentive, consistent with the likelihood that such households have insufficient tax liability to fully benefit from the FTC. Even more broadly, *no* household or regional characteristics studied were associated with the odds of being an *FTC Extreme*. *Rebate Essential* and *EV Convert* status are similarly not predicted by most household characteristics (in those two cases, having solar tends to reduce the odds; for *Rebate Essential,* residing in California's Central Valley tends to increase the odds).

Motivationally speaking, the convenience of charging does not help explain *FTC Extreme, Rebate Essential,* or *EV Convert* status for PHEV consumers. Modelling of *FTC Extremes* also included the importance of charging availability on the way to other locations (i.e. not home or work), but, perhaps due to collinearity with importance of charging at other places, that was not found to be significant. Vehicle performance is also not predictive for any of the three PHEV segments, and *FTC Extreme* status was not found to be associated with the desire for new technology. Lower initial interest in EVs, the definition of an *EV Convert*, does not help predict *Rebate Essentiality* or *FTC Extreme Importance* for PHEV consumers. This might mean that these incentives have recently not been "converters" of consumers into having interest in an PHEV, so much as enablers of purchases by at least moderately interested shoppers.

The differences between the descriptive findings in Table 2 and the predictive findings in Table 3 are also notable: race/ethnicity, age, and income are all significantly different for the *PHEV FTC Extreme* segment when examined one at a time, but none of those factors explains segment status when controlling for other variables in the logistic regressions.

4.3 Dominance Ranking Results & Discussion

Dominance analysis is used to understand the relative importance of significant variables (e.g., using Estrella pseudo-R^2). Table 4 ranks the average contribution of significant predictors for the Parsimonious PHEV Model.

Table 4: Summary and Rank-Ordering of Key *PHEV FTC Extreme* Predictors (Dominance Analysis)

Variable Description	Odds-Increasing Examples (see Table 3)	Average of Pseudo-R^2 Average Contributions	Rank
Importance of saving money on fuel	Very or extremely important (vs. Not)	0.045	1
Importance of charging availability at work	Very or extremely important (vs. Not)	0.039	2

Importance of carpool/HOV lane access	More important	0.027	3
Importance of charging availability at/near destinations other than home and work	Very or extremely important (vs. Not)	0.027	4
FTC incentive amount ($1,000s)	Larger amount	0.022	5
Importance of charging availability at home	Extremely important (vs. Not) Not important (vs. Slightly)	0.020	6
Vehicle make	Not Chevrolet nor Honda (vs. others)	0.011	7
Importance of increased energy indepndnce	Extremely important	0.007	8
Purchase quarter	Later in year	0.006	9
Education	Higher educational attainment	0.005	10
Purchase price	Lower price	0.004	11
Tax filing status	Single (vs. Married filing separately)	0.003	12
Gender	Male	0.001	13

Most of the top predictors of PHEV consumer Extreme FTC Importance relate to placing importance on financial savings or charging availability of various types. The predictors with the highest average contribution to explaining the *FTC Extreme* segment are financial. It should be noted that several financial factors were intentionally removed due to theoretical considerations, such as the conceptual overlap with the outcome variable. For example, it is unsurprising that FTC Extreme Importance is associated with giving higher importance to saving money overall and rating the state rebate essential. These factors dominated models when present, making the results almost trivial. When removed, several other predictors emerged, but financial variables were still prominent among the results, including the high importance placed on saving money on fuel (#1) and the amount of the tax credit for which the purchased PHEV was eligible (#5). An additional factor arguably related to financial benefit, although with a modest contribution, is the timing of the vehicle purchase in the calendar year (purchase quarter, #9)—given that the later in the year the purchase is made, the sooner the tax credit savings will be realized. Also important to the explanation of *PHEV FTC Extremes* are the high importance those consumers also place on charging availability: at work (#2), at non-home/non-work destinations (#4), and at home (#6). Placing more importance on carpool-lane access (#3) is also a major contributor, and a typically important nonfinancial incentive for EV adopters [2,8,9]. Rounding out the explanatory factors with significant, albeit modest, explanatory contributions (2 to 45 times smaller than the top 6 factors) are: non-Chevrolet/non-Honda vehicle make (#7), the extreme importance of increased energy independence (#8), higher educational attainment (#10), lower vehicle purchase price (#11), single tax-filing status (vs. married filing separately, #12), and male gender (#13).

5 Summary, Caveats & Conclusions for Supporting EV Markets

How important has the Federal Tax Credit (FTC) been, and who found it most enabling of their purchase of a plug-in hybrid electric vehicle (PHEV)? This ongoing research used descriptive statistics and logistic regression to identify characteristics associated with rating the FTC "Extremely Important." Factors explored for their ability to help predict which consumers might be "*FTC Extremes*" included demographic, household, and regional characteristics; purchase motivations; and vehicle-transaction details. A majority of rebated survey respondents rate the FTC as extremely influential (Table 1). This majority is increasing, a trend that in and of itself is telling, because it runs counter to typical paradigms about phasing-out of EV incentives over time [3]. Summarized descriptively (Table 2), *FTC Extremes* appear similar to new-car buyers in terms of race/ethnicity and age. They also appear to be distinct from consumers without extreme FTC importance in terms of educational attainment and income. However, when *FTC Extreme* segment membership is explained using logistic regression that controls for other variables, age, race/ethnicity, and income were not statistically significant predictors of FTC

Extreme Importance—neither were any household and regional characteristics examined, nor the appeal of vehicle performance or new technology.

FTC Extremes were found to be highly motivated by financial savings and charging availability, along with carpool-lane access (Table 4). It is not surprising that placing extreme importance on an incentive goes hand-in-hand with the size of that incentive, the importance of other financial benefits such as saving money on fuel, and prerequisites for realizing those benefits, such as charging availability. But the predominance of these factors in explaining segment membership is such that it paints a very practical, arguably single-minded, focus on PHEVs as metaphorical vehicles of tangible, direct benefits rather than the reduced environmental impacts that highly motivate EV adopters overall. Indeed, choosing environmental impacts as the *most* important reason motivating the PHEV purchase *reduced* the odds of being *FTC Extreme* in the Full Model. Further, other predictors significant in the Full Model that did not survive the reduction down to the Parsimonious Model (section 3) include: being highly influenced by state EV rebates (*Rebate Essentials*) and not having received an increased state rebate that is only available to consumers with household incomes too low to fully benefit from the FTC.

This financial and practical-use focus is also reinforced by findings indicating reduced odds of being *FTC Extreme* when buying PHEV brands that are more “BEV-like” (the Chevrolet Volt and Honda Clarity PHEV), compared to more “hybrid-like” (the Toyota Prius Prime and luxury PHEVs). This is consistent with conceptions of the latter category as high-MPG/high-efficiency fuel savers more than transformational and socially beneficial all-electric products. Finally, *FTC Extremes* exhibit very faint echoes of characteristics seen in *Rebate Essentials,* such as higher educational attainment, purchase of lower-priced vehicles, and being somewhat more frequently male (albeit with almost trivial contributions being made by those factors).

One variable that increased the odds of being *FTC Extreme* and is unrelated to personal benefits is placing extreme importance on increasing energy independence. However, this factor provides a substantially lower contribution to the explanatory model than predictors related to practical, direct benefits.

Caveats. Although based upon large datasets characterizing major portions of California’s nation-leading EV market, this work is first and foremost applicable to efforts to optimize CVRP by taking into account the FTC and its influence. Analyses using similar rebate-program datasets from three Northeastern U.S. states (Massachusetts, Connecticut, and New York) have tended to show more commonalities across states than differences, at least to-date using relatively aggregated measures of program participation and impact [23]. However, interpretation should be done with caution and be mindful of CVRP’s program features and California’s unique market. Further, the uniqueness and recent dominance of Tesla in the market warrants separate modelling of both Tesla and non-Tesla BEV groups. Finally, analysis of program non-participants is critical to understanding key barriers to market entry that may be standing in the way of “potential *FTC Extremes*.”

Nevertheless, it is hoped the results presented here help increase understanding of FTC influence. As noted previously, additional work remains to understand BEV consumers. Also, continued removal or rebalancing of related financial and charging-availability predictors currently in the model could further amplify a more complete, nuanced, and actionable array of consumer characteristics associated with being highly influenced by the FTC.

In the meantime, Table 4 provides the key findings for moving forward, by rank-ordering the most important predictors by their contribution to explaining *PHEV FTC Extremes*. These predictors represent the clearest distinguishing features. They also allow comparison to recent findings about other strategic market segments, such as *Rebate Essentials*—who are cost-effective targets for incentive programs aimed at reducing free ridership and encouraging true additions to join the EV market—and *EV Converts*—who had low initial interest in EVs and represent a path toward more mainstream markets. For example, PHEV-purchaser FTC Extreme Importance is not associated with the low-initial interest in EVs that define *EV Converts*. Rather *PHEV FTC Extremes* appear to be consumers who are already “pre-converted” [21] to be interested in EVs by incentives and other promises of financial and practical benefits. Like *Rebate Essentials*, *FTC Extremes* may be a reasonable proxy for *FTC Essentials*: they may *need* such benefits to get them to act on their interest to join the EV market. Having done so, *FTC Extremes* bring with them a unique combination of market-expanding characteristics. For example, they are more mainstream than enthusiastic early adopters of EVs along some dimensions, but not to the same extent as *EV Converts.* Similarly, they share some but not all features with *Rebate Essentials*, and the contribution of some of those shared features to the odds of being *FTC Extreme* are faint. Like research on *Rebate Essentials*, increasingly sophisticated profiles of *FTC Extremes* will similarly increase understanding of who is most highly influenced by incentives. This will not only improve assessments of the impact of the FTC, it will improve incentive designs that cost-effectively stretch the boundaries of current adoption and grow EV markets further into the mainstream.

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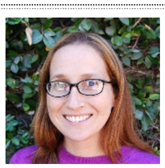

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