Strategically Targeting Plug-in Electric Vehicle Rebates and Outreach Using Characteristics of "Rebate-Essential" Consumers in 2016–2017

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ABSTRACT: Public and private investments to increase electric-vehicle (EV) awareness and adoption seek to be strategic, cost-effective, and minimize free-ridership. Building upon previous research, this work uses logistic regression to examine the relationship between rebate influence and consumer factors (demographic, household, and transaction characteristics; motivations; and experience). Using 2016–2017 data characterizing rebated California plug-in EV consumers (n=5,340), it models adopters of battery EVs and plug-in hybrid EVs separately to capture their unique qualities and circumstances. Changes relative to 2013–2015 data are discussed relative to expectations. Findings inform targeted marketing/education/outreach efforts, incentive program design, and other supportive policies.

KEY WORDS: electric vehicle (EV) consumer characteristics, target market segments, strategic outreach, incentive design, free riders

1. INTRODUCTION

1.1. Problem

The market share of plug-in electric vehicles (PEV) remains modest despite substantial public and private investments to promote PEV awareness and adoption. The targeting of supportive resources, such as marketing/education/outreach and incentives, increasingly aims to strategically and cost-effectively encourage consumers to enter the PEV market while minimizing free-ridership by those who require no support.[(1)] Where should such efforts focus?

1.2. Previous work

Published analysis of PEV target market segments has included characterization of California consumers who were the most highly influenced by rebates to purchase or lease plug-in hybrid electric vehicles (PHEVs) during the 2013–2015 timeframe.[(2)] It used binary logistic regression to examine the relationship between consumer factors—transaction, household, and demographic characteristics, motivations, and experience—and the influence of the rebate on their acquisition decision, i.e., if they would have purchased their vehicle without the rebate.

1.3. Contributions and overview

This work: 1) updates that perspective on "*rebate-essential*" PHEV consumers with 2016–2017 data (n=2,235) and 2) adds characterization of battery-electric-vehicle (BEVs) consumers (n=3,105), modeled separately to capture their unique circumstances. These results are compared to each other, and to similarly constructed models using 2013–2015 data (n=7,323 for PHEVs and 10,852 for BEVs), resulting in a total of four models.

In section 2, the data and consumer characteristics are summarized and representativeness discussed. In section 3, modeling methods are summarized, including data preparation, variable selection, model specification and other considerations. Notably, the majority of 2016–2017 consumers received rebates after a major program change in 2016 that limits rebate eligibility based upon consumer income. Accordingly, the dataset is trimmed to make the group homogenous with respect to program era. Next, the results are presented in section 4. For each consumer group (PHEV and BEV adopters) and each market/program era (2013–2015 and 2016–2017), characteristics associated with being *rebate-essential* are presented. Further, characteristics of the more recent consumers are ranked by standardized effect. In section 5, these results are discussed. Comparisons are made to highlight changes over time and the differences between target PHEV and BEV consumers. Select limitations are presented. Finally, summary conclusions are drawn, including discussion of implications for outreach strategy and rebate program design.

2. SUMMARY OF EV CONSUMER DATA

2.1. Data

The Clean Vehicle Rebate Project (CVRP) provides rebates to California consumers for the purchase or lease of light-duty PHEVs, BEVs, and fuel-cell electric vehicles (and zero-emission motorcycles, from whom survey data is not yet collected). To improve understanding of the program and the burgeoning EV market more generally, CVRP has administered a voluntary Consumer Survey of private-individual (i.e., not fleet) participants since 2013. The Consumer Survey covers topics including: interest in and research on EVs, sources of information used, decision-making process, dealership experience, housing characteristics, and demographics. Participants receive a survey invitation by email with the notification that their application has been approved, and receive a reminder invitation with the subsequent notification that their rebate check has been sent. Data from two editions of the CVRP Consumer Survey (excluding fleet and FCEV participants) are utilized in this work and summarized in Table 1.

Table 1. Summary of CVRP PEV Survey Data.

Consumer Survey (private individuals only)	**2013–2015 edition**	**2016–2017 edition** (FCEV responses removed)
Timeframe		
Administration Dates	10/25/2013–06/23/2015	07/19/2016–08/31/2017
Vehicle Purchase/ Lease Dates	09/01/2012–05/31/2015	05/01/2016–05/31/2017
Sample Size and Representativeness		
Program Participant Population	N = 91,081	N = 46,839
Responses in Dataset	n = 19,460 (21%)	n = 8,957 (19%)
Weighting Method	Raking	
Representative Dimensions	Vehicle model, purchase vs. lease, county of residence	
Program as a % of PEV Market*	~69%	~51%

*There were 131,262 new PEVs registered in California 9/2012–5/2015 and 92,334 registered 5/2016–5/2017.[3]

2.2. Representative consumer characteristics

Because the Consumer Survey is voluntary and not all participants choose to complete the survey, responses may not be perfectly representative of CVRP as a whole. However, using application information provided by all participants, response weights have been calculated using the raking method to make each edition of the Consumer Survey data representative of all program participants during its respective time frame along the dimensions of vehicle model, purchase vs. lease, and county of residence.

These weights are regularly used elsewhere. For example, all responses to the 2013–2015 edition are summarized and weighted in survey documentation available on the program website[4], and many of the weighted results are available in a dynamic CVRP public data dashboard[5]. Use of weights over time has regularly shown results modestly different (e.g., by a few percentage points or less) from use of the unweighted data.

For purposes of targeting incentives and related outreach, CVRP participants are a population of immediate interest. For those with broader interests, CVRP is not necessarily representative. However, CVRP participants have historically constituted a majority of the California PEV market (Table 1)

Select information about, and results from, the 2016–2017 edition is contained in presentations and analysis on the CVRP website[6], which is updated regularly. For illustration, the majority of the 2016–2017 participants had the following characteristics (individually, not in combination):

- *Housing*: detached homes = 77%
- *Household income*: less than $150,000 per year = 58%
- *Age*: 40–59 years old = 51%
- *Education*: College degree or more = 81%
- *Gender*: male = 72%
- *Ethnicity*: white/Caucasian = 61%

More nuanced characterizations of these consumers represent a baseline for the recent adopter population. Analysis to identify a promising target segment of that population is described next.

3. *REBATE-ESSENTIAL* MODELING

This section describes the approach taken to data preparation and to binary logistic regression modeling of characteristics associated with being highly influenced by the vehicle purchase/lease rebate.

3.1. The model

The outcome variable is a binary variable indicating whether consumers are either "*rebate-essential*" (coded as 1) or rebate-non-essential (coded as 0), based on survey responses to the question, "Would you have purchased or leased your [PEV model] without the state rebate (CVRP)?" Respondents who would not have purchased without the rebate are considered *rebate-essential*. Cases missing a response were deleted from the analysis (a total loss of 69 cases, or 1.2% of the original 2016–2017 sample).

The predictor variables. Analysis variables were drawn primarily from the Consumer Survey, but were also supplemented by vehicle and consumer data drawn from CVRP applications. Variables were selected primarily for their theoretical relevance and serviceability as program and policy levers. The final set of variables tested for inclusion appears in Table 2.

3.1. Data preparation for modeling

Unweighted data are used for the logistic regressions. Because the response weights are not a function of the outcome variable (rebate essentiality), the unweighted responses were preferred for modeling due to having smaller standard errors and being unbiased and consistent when used to estimate causal effects.[7]

PHEV and BEV adopters are treated separately. Research on the effect of incentives has also indicated that effects may vary by vehicle technology.[8,9] While this is attributable in part to substantial differences in incentive levels afforded to differing technology types, it is also related to more fundamental differences in the resulting products and their associated adoption requirements and use behaviors. Documented differences in new-vehicle markets and consumer segments associated with PHEVs vs. BEVs include consumer demographic, psychographic, and housing characteristics, and well as driving and charging use behaviors.[10-14] In consideration of these differences, this research examines consumers of each vehicle type separately (building upon examination of 2013–2015 PHEV data in prior work.[2]

Pre-income-cap purchases were trimmed from the 2016–2017 dataset. The majority of survey responses in the new dataset were for vehicles rebated after introduction of income-based rebate eligibility. These features, which included limits on the income of eligible consumers and the creation of an Increased Rebate for lower-income consumers, took effect in March 2016 and were adjusted 1 November 2016, as described on the program website.[15] In order for the data to represent a cohesive group, 3,341 respondents who adopted before November 2016 were removed, leaving only those of the current era.

Missing data and multiple imputation. As is common with survey data, a number of data points were missing due to non-response. The proportions of missing data by variable also appear in Table 2. A high proportion of missing data occurs for the variable measuring household income, but the missingness rate (nearly 12%) is less than rates achieved in other surveys.[16] Non-response on household income questions are unsurprising, but can still pose an obstacle to valid data analysis.

Additionally, a question asking respondents to characterize the ease with which they obtained information online about EV ownership also had a high non-response rate (almost 16%). This may have been related to survey design and respondent fatigue—respondents were asked to rate their experience finding information about nine topics using a five-point Likert scale (four of which were averaged, where available, for this analysis).

For the other variables displayed, rates of missingness were less than 3%, as illustrated in Table 2 (which combines PHEVs and BEVs but is illustrative of rates for each).

Missing data were addressed in three stages for each of the PHEV and BEV consumer datasets:

1. For variables with values missing for less than 1% of cases, listwise deletion was applied, checking that the total loss to sample size was roughly 5% or less.
2. For the remaining missing values, multiple imputation was applied with 20 iterations.

The use of multiple imputation was primarily motivated by the income variable, for which missingness is expected to be related to the outcome variable and therefore not assumed to be missing completely at random (MCAR). Listwise deletion of data missing conditionally at random (MAR) or not missing at random (NMAR) can result in biased estimates. However, single imputation methods underestimate the variance of the estimates and can result in Type I errors as a result of overly narrow confidence intervals. Multiple imputation uses multiple (in this case, 20) imputed datasets to generate variability and thus address this limitation of single imputation.[17]. Therefore, multiple imputation was selected as the preferred approach to address remaining missing data, in order to maximize the validity of statistical results. While multiple imputation is regarded as a preferred approach, the large proportion of missing data for two variables should be taken into consideration when interpreting the results.

The final datasets. After deleting cases and imputing missing values, the sample went from 2,339 PHEV consumers to a final sample size of n=2,235, and from 3,277 to n=3,105 for BEVs.

4. RESULTS

4.1. Odds Ratios, Standardized Odds Ratios, and Significance

After imputation of missing values, the variables listed in Table 2 were used in a logistic regression analysis to predict the likelihood of identifying as a *rebate-essential* PHEV or BEV consumer.

Table 2. Variables and Model Results.

#	Variable Description	Example Values	Missing %	Odds Ratio, PHEV '16–17	Std. O.R.	O.R., PHEV '13–15	O.R., BEV '16–17	Std. O.R.	O.R., BEV '13–15
-	Rebate essentiality (outcome variable)	1=rebate essential; 0=not rebate essential	1.2%	n.a.	n.a.	n.a.	n.a.		n.a.
1	Date of purchase	11/1/2016–5/31/2017	0%	1.001	1.19	0.9998	1.001		1.001*
2	Time btwn purchase & survey response	9–264 days	0%	0.997*	0.81	0.9996	0.9997		1.0001
3	Price	$12,700–$165,200	0%	0.9999*	0.60	0.99998*	0.99998*	0.32	0.99999*
4	Purchased or leased	1=purchased; 0=leased	0%	0.89		1.27*	1.03		0.99
5	Vehicle replaced or added to household	1=replaced; 0=added	0.3%	1.22		0.96	0.85		0.95
6	Residence ownership	1=own; 0=rent	2.7%	1.08		1.06	0.89		1.03
7	Residence type	1=multi-unit dwelling; 0=detached house	1.4%	1.15		1.06	1.08		1.20*
8	PHEVs: Ford (vs. Chevrolet)	1=true; 0=false	0%	0.76*	0.81	0.73*	(PHEV)	(PHEV)	(PHEV)
9	PHEVs: Toyota (vs. Chevrolet)	1=true; 0=false	0%	0.72*	0.74	0.90	(PHEV)	(PHEV)	(PHEV)
10	PHEVs: Other (vs. Chevrolet)	1=true; 0=false	0%	1.22		0.55*	(PHEV)	(PHEV)	(PHEV)
11	BEVs: Tesla (vs. Nissan)	1=true; 0=false	0%	(BEV)	(BEV)	(BEV)	1.15		0.67*
12	BEVs: FIAT (vs. Nissan)	1=true; 0=false	0%	(BEV)	(BEV)	(BEV)	1.44*	1.36	0.97
13	BEVs: Chevrolet (vs. Nissan)	1=true; 0=false	0%	(BEV)	(BEV)	(BEV)	0.36*	0.41	0.72*
14	BEVs: Other (vs. Nissan)	1=true; 0=false	0%	(BEV)	(BEV)	(BEV)	0.82		0.68*
15	Bay Area (vs. Central)	1=true; 0=false	0%	0.48*	0.51	0.78	0.32*	0.33	0.54*
16	Central Coast (vs. Central)	1=true; 0=false	0%	0.86		0.92	0.36*	0.68	0.62*
17	Far South (vs. Central)	1=true; 0=false	0%	0.78		0.89	0.33*	0.49	0.65*
18	North (vs. Central)	1=true; 0=false	0%	0.59	0.77	0.93	0.43*	0.67	0.59*
19	South (vs. Central)	1=true; 0=false	0%	0.56*	0.56	0.82	0.30*	0.30	0.53*
20	Disadvantaged Community (CES 2.0 def.)	1=DAC census tract; 0=other census tract	0%	0.82		0.95	0.59*	0.75	0.90
21	Solar - no, but planning (vs. yes)	1=yes; 2≈no, but plans; 3≈no and no plans	0.5%	1.16		0.98	1.02		1.16*
22	Solar - no, not planning (vs. yes)	1=yes; 2≈no, but plans; 3≈no and no plans	0.5%	1.32*	1.30	0.95	1.05		1.16*
23	Age	1= 16-20; 2= 21-29; …; 7=70-79; 8=80+	1.9%	0.91*	0.76	0.95	0.91*	0.78	0.99
24	Male	1=male; 0=female	2.2%	1.24*	1.22	1.36*	1.05		1.18*
25	White	1=white; 0=non-white	0.02%	0.65*	0.66	0.79*	0.89		0.82*
26	Bachelor's degree (vs. postgrad)	1=Associate degree or less; ...; 3≈Postgrad.	0%	0.96		0.93	0.92		0.91*
27	Associate degree or less (vs. postgrad)	1=Associate degree or less; ...; 3≈Postgrad.	0%	0.76*	0.80	0.83*	0.62*	0.69	0.78*
28	Income (bin)	1–11 (increasing in $50,000 increments)	11.9%	0.98		0.94*	0.92*	0.75	0.96*
29	Importance: save on fuel costs	1=not at all important; ... 5≈extremely	1.8%	1.14*	1.28	1.23*	1.30*	1.79	1.34*
30	Importance: environment	1=not at all important; ... 5≈extremely	1.2%	0.94		0.93*	0.85*	0.71	0.95*
31	Importance: carpool	1=not at all important; ... 5≈extremely	1.5%	1.12*	1.35	1.05*	1.16*	1.56	1.12*
32	Importance: energy independence	1=not at all important; ... 5≈extremely	1.6%	1.05		1.09*	1.03		0.96
33	Importance: vehicle performance	1=not at all important; ... 5≈extremely	1.8%	0.97		1.002	0.94		0.97
34	Importance: Convenience of charging	1=not at all important; ... 5≈extremely	1.7%	0.99			1.10	1.21	
35	Lower-income Increased Rebate	1=increased rebate; 0=no increased rebate	0%	1.93*	1.48		1.998*	1.52	
36	Initial interest in a PEV	0≈unaware; 1≈none; ...; 3≈very; 4≈only	0.3%	0.92	0.84	0.71*	0.96		0.78*
37	Heard about CVRP from the dealer	1≈heard from the dealer; 0≈elsewhere	0.9%	0.76*	0.76	0.85*	0.66*	0.64	0.86*
38	No workplace (vs. no WPC)	0=no workplace charging; ...; 2≈yes WPC	1.4%	0.91		0.90	1.06		0.79*
39	Workplace charging avail. (vs. no WPC)	0=no workplace charging; ...; 2≈yes WPC	1.4%	0.97		1.07	0.87		0.84*
40	Previous PEVs owned	0–3+	0.4%	1.12		0.91	0.93		1.04
41	Drivers in household	1–9+	1.6%	0.99			0.88	0.81	
42	Time spent researching (online)	1≈none; 2≈ <4 hours; ...; 4≈ >12h	0.7%	1.11*	1.23	1.22*	1.01		1.19*
43	Not charging at home	1=true; 0=false	1.1%	0.92			0.97		
44	Years of intended ownership	1–20	1.0%	1.02			1.03		
45	Cars in household	1–4+	1.6%	1.11			1.09		
46	Number of people in household	1–9+	1.6%	1.01		1.03	1.04		1.07*
47	Ease of finding information online	[1–5 scale; ave. across 1–4 questions]	15.8%	0.83*	0.74	0.82*	0.77*	0.64	0.85*

For ease of interpretability, odds ratios (O.R.) are reported in Table 2. Expressed as odds ratios, the regression coefficients show the multiplicative change in the odds of being *rebate-essential* if the predictor variable of interest increases by one unit, holding all other predictor variables constant. An odds ratio not statistically significantly different from one (unity) therefore shows a lack of an effect. 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.

Odds ratios are particularly intuitive for binary variables. For example, holding all other variables constant, if identification as male has an odds ratio of 1.24 (variable #24 for PHEV consumers during 2016–2017), it is associated with a 23% increase in the odds of being *rebate-essential*. Coefficient values, whether presented as odds ratios or log odds, should *not* be compared across predictor variables, due to differing units of measurement and variance. For example, a one-unit change in vehicle price (one dollar) is not directly comparable to a one-unit change in purchase date (one day).

To facilitate comparison across predictors, standardized odds ratios were produced for each of the PHEV and BEV models using 2016–2017 data. These show each predictor's effect per an increase that is the size of one standard-deviation for that predictor. They can be used to rank the relative importance of the predictors: those farthest from one having the most impact when they change by one standard deviation, holding everything else constant.

Significance is tested to the 95% level ($p < 0.05$) and indicated by an asterisk and green shading on the odds ratio of significant predictor variables for a given model. Additionally, four instances of variables with $p \leq 0.060$ are differently shaded with no asterisk, in order to highlight candidates that were found to be significant in exploration of more parsimonious or alternative model specifications. For example, exploratory work on a more parsimonious model with the least theoretically compelling non-significant variables removed led to the significance of purchase/lease date.

In addition to the significance tests associated with each value of the categorical variables displayed in Table 2, each categorical variable was tested for its overall significance to the model by testing whether the coefficients for the categories were jointly zero.

4.2. *Rebate-essential* PHEV consumers, 2016–2017

Table 3 summarizes the significant characteristics for recent PHEV consumers, rank-ordered using their standardized odds ratios and expressed so all factors are associated with increasing rebate essentiality.

Table 3. Ranked significant predictors - PHEV consumers.

Rank	Odds-increasing factors
1.954	Reside in Central region (vs. Bay Area)
1.793	Reside in the Central region (vs. South)
1.663	Acquiring lower-price vehicle
1.517	Are non-white
1.479	Eligible for Increased Rebate
1.358	Had difficulty finding PEV info online
1.348	More motivated by carpool-lane access
1.347	Acquiring a Chevy PHEV (vs. Toyota)
1.309	Are younger
1.308	Heard about CVRP elsewhere than dealer
1.302	Do not have solar
1.285	More motivated by saving on fuel costs
1.258	Have higher educational attainment
1.239	Acquiring a Chevy PHEV (vs. Ford)
1.235	Receive rebate sooner after purchase
1.228	Spent more time searching online
1.221	Are male
1.194	Have a lower initial interest in PEVs
1.191	[rebate importance continues to grow]

Factors common with BEVs are in blue font. It should be noted that both the solar category (p = 0.076) and education category (p = 0.094) were not jointly significant, weakening the significance of the individual variables in those categories.

Table 4. Ranked significant predictors - BEV consumers.

Rank	Odds increasing factors
3.350	Reside in Central region (vs. South)
3.078	Acquiring lower-price vehicle
3.066	Reside in Central region (vs. Bay Area)
2.413	Acquiring a Nissan BEV (vs. Chevy)
2.033	Reside in Central (vs. Far South)
1.790	More motivated by saving on fuel costs
1.559	Had difficulty finding PEV info online
1.558	More motivated by carpool-lane access
1.553	Heard about rebate elsewhere than dealer
1.517	Eligible for Increased Rebate
1.499	Residing in Central (vs. North)
1.467	Residing in Central region (vs. Central Coast)
1.457	Have higher education attainment
1.411	Less motivated by reducing environmental impacts
1.357	Acquiring a FIAT BEV (vs. Nissan)
1.331	Reside outside of a CES 2.0 Disadvantaged Community
1.330	Have lower income
1.289	Are younger
1.213	More motivated by the convenience of charging

4.3. *Rebate-essential* BEV consumers, 2016–2017

Table 4 summarizes the significant characteristics for recent BEV consumers, rank-ordered using their standardized odds ratios and expressed so all factors are associated with increasing rebate essentiality. Factors common with PHEVs are in blue font.

4.4. *Rebate-essential* PHEV and BEV consumers, 2013–2015

Table 2 provides the odds ratios for the models using 2013–2015 data and differences with the 2016–2017 consumes are discussed in section 5. A comparison was made between Table 2 and prior PHEV modeling by Johnson and Williams.[(2)] No major differences were found, making Table 2 a reasonable proxy for that prior work. Further, exploratory work on a more parsimonious models did not lead to major differences.

5. DISCUSSION

Most of the findings support discussions detailed in previous research that are not repeated here due to space limitations.[(2, 18)] But what has changed? The overall time trend appears to be that of diminishing odds ratios and significance. Notable examples include:

- The insignificance of buy vs. lease (#4), consistent with trends towards high levels of leasing across technology types.
- The insignificance of energy independence as a motivator (#32) (with an increased focus on fuel cost savings [#29] and carpool lane access [#31]), consistent with a national shift away from conversation about imported oil.
- The diminished prominence of income (#28), likely related to at least three factors: 1) the rebate-program income limits ($150,000 per year for single tax filers, $300,000 for joint filers), 2) the inclusion in the models of a dummy variable for receipt of the Increased Rebate (#35, for individuals living in households with incomes that are 300% or less of the Federal Poverty Level), and 3) the evolution of the income distribution of PEV adopters over 2 years of market evolution
- The insignificance for BEVs of several housing-related factors (housing type [#7], solar [#21–22], workplace charging [#39–39], and number of people in household [46]), perhaps as BEVs become less compromised, less in need of accommodation, and more widely accepted/accessible? Might this might be supported by the loss of significance of gender (#24) and ethnicity (#25) factors for BEVs??

Notable additions, on the other hand, include:

- An expected significance for variable #2, which measures the time between the purchase and approval for a rebate (which triggers the survey invitation), and thus a consumer's willingness to "float" the expense until being reimbursed
- The significance of geography (#15, 19) for PHEV consumers, which is considered consistent with the relative overall level of exposure to PEVs and supportive resources experience by the regions (e.g., a PEV dense and enthusiastic San Francisco Bay Area vs. a more rural and traditional Central Valley [#15]). This factor is prominent for BEVs, which represent a more radical behavioral departure.
- The significance of younger age (#23) for BEV consumers (as well as for PHEVs), expected for less well-established consumers.

It should be noted that exploration with more parsimonious models of the newer consumers (e.g., which did not include three out of the six variables found only in the new dataset) did not increase the similarities between the old and new consumer models in any substantial way.

6. CONCLUSIONS

There are several ways to increase EV adoption. Marketing/incentive efforts aimed a growing the market for EVs by reinforcing current trends, described elsewhere as "adding fuel to the fire"[(18)], can focus on recruiting consumers that are similar to past EV consumers, who often are "pre-adapted" to adopt.[(19)] For example, the characteristics of the 2016–2017 consumer population briefly summarized in section 2 constitute a profile of relatively recent adoption in California.

On the other hand, strategic targeting of marketing/incentives at consumers that are the most highly influenced by incentives to enter the market is an example of "expanding market frontiers"[(18)]. This approach seeks to identify the segments of the current adopter population that can be cost-effectively leveraged, and perhaps might represent the margin that points the way towards more mainstream expansion. This work identifies consumer characteristics that help strategic planners pivot, from the starting point of the baseline profile of current adopters, in order to increase the odds that supportive resources will find potential adopters most influenced to buy/lease a PEV.

Specifically, the top factors are, in rank order, to seek out consumers that are: more motivated by fuel cost savings, residing in areas like California's Central Valley, acquiring a lower-price vehicle, more motivated by carpool-lane access, eligible for an Increased Rebate for lower-income consumers, having difficulty finding PEV information online, finding out about incentives before going to the dealership, and who have higher educational attainment. By adjusting target-consumer profiles to take these factors into account, it is hoped that resources will cost-effectively find a margin of overlap between what is already working in the PEV market and where we might desire the market to be.

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