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Research paper

Understanding potential for battery electric vehicle adoption using large-scale consumer profile data



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ABSTRACT

Ten U.S. states have set mandated sales targets for zero-emission vehicles that could result in significant reductions in fuel consumption and carbon emissions. Battery electric vehicle (BEV) adoption is considered integral to achieving this mandate and thus a better understanding of potential BEV buyers is needed. Because of limitations of stated-preference surveys, we developed a data mining approach to identify potential buyers using revealed-preference data. We apply the approach to a nationally representative survey of 88,404 new car buyers that includes respondents' geographic, demographic and psychographic characteristics. We find that BEVs have the potential to reach an annual U.S. market share of 2.4%. To achieve this, BEVs with added features must be sold at a lower price. The costs of the improved features combined with the eventual removal of purchase subsidies will offset the forecasted declines in battery costs. BEVs face stiff competition from fuel-efficient gasoline vehicles and thus policies promoting their sales such as the fuel economy standards may reduce BEV's growth.

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1. Background

Light duty vehicles (LDVs) in the United States account for about 42% of liquid fuel consumption, and 17% of total U.S. energy related CO₂ emissions (EIA, 2015). Although fully-electric, battery electric vehicles (BEVs) comprised only ~0.38% of total new LDV sales in 2014, if adopted at a large scale, they could substantially reduce U.S. liquid fuel consumption and greenhouse gas (GHG) emissions (Greene et al., 2014; Chapin et al., 2013).

Ten U.S. states, including California, representing 28% of total U.S. LDV sales (NRC, 2015), have set a target of 3.3 million cumulative sales of zero-emission vehicles (ZEVs) by 2025. The target, known as the ZEV Mandate, entails major techno-economic and policy spillovers for the rest of the U.S. and the world (Sperling and Eggert, 2014). From GHG emissions perspective, the ZEV mandate in California is aligned with the state's executive order S – 03 – 05 requiring a reduction in state-wide GHG emissions to 80% below 1990 levels by 2050, which would require ZEVs to reach 100% of new vehicle sales by 2050 (CARB, 2012). Among the different ZEVs considered, this paper focuses on BEVs, the most widely adopted pure zero tailpipe emission technology to date in the U.S.

For BEV adoption to be successful, stakeholders need a better understanding of consumers: namely their preferences, attitudes and decision-making (Greene et al., 2014; Chapin et al.,

2013; NRC, 2015; Collantes, 2010; Hardman et al., 2018, 2017; Axsen et al., 2015). LDV adoption initiatives that do not address consumer needs might prove out to be unsustainable.

Technology adoption literature emphasizes that as new technology enters the market, different segments of buyers will adopt in phases; not all buyers switch at the same time (Rogers, 2010). From a marketing perspective, a strategy to promote new technology adoption ought to target segments of consumers who will be more inclined to using the new technology (Slater and Mohr, 2006). Policies and targets that promote BEVs that do not take into account the relative size of potential buyers in the market and their needs and preferences risk being unsuccessful or unsustainable. Thus, there is a need to study potential buyers rather than mass-market buyers. Additionally, we must understand how BEVs and other alternative fuel vehicles (AFVs), such as plug-in hybrid electric vehicles (PHEVs), compete over this crucial segment of the market.

2. Introduction

Studying potential buyers of BEVs can be done through a stated preference survey wherein consumers are asked about their interest in purchasing a BEV in the future. For example, stated preference surveys have been used to study adoption barriers for electric vehicles among potential buyers (Egbue and Long, 2012), lifestyle and preference heterogeneity among potential buyers (Axsen et al., 2015), and what attributes of electric

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vehicles (EVs) car-buyers valued (Caulfield et al., 2010; Axsen and Kurani, 2013). They have also been used to estimate consumer interest and willingness to pay (Carley et al., 2013; Hidrue et al., 2011; Potoglou and Kanaroglou, 2007; Kihm and Trommer, 2014).

However, in stated preference experiments, consumers might misrepresent their choices, as they tend to react differently to hypothetical choice experiments than they would facing the same alternatives in a real market (Brownstone et al., 2000). People may (consciously or unconsciously) overstate their intention to make purchases that are perceived to be in favor of the environment (Brownstone et al., 2000). Thus, results based on stated preference may be biased and over-estimate the desirability of BEVs.

Revealed preference surveys of current BEV adopters capture needs and preferences without the biases associated with stated preference studies. For example, revealed preference surveys have been used to assess the motivations of AFV buyers (Ozaki and Sevastyanova, 2011; Tal et al., 2013). Understanding people who have already purchased a BEV can provide useful context, but does not directly address nor identify potential adopters.

Because of these limitations, we developed a data mining approach, *ex-post* counterfactual inference, which can identify potential buyers using revealed preference data. This is the first time the method has been used in any field and has broad applications for the analysis of revealed preference survey data and technology adoption. We apply the approach to a nationally representative large-scale survey of 88,404 new car buyers that includes respondents' geographic, demographic and psychographic characteristics. We seek to answer four main questions: (i) who buys BEVs and for what reasons, (ii) who might buy BEVs and how many of them are in the market, (iii) what factors can induce them to buy, and, (iv) to what extent are BEVs competing with other AFVs and fuel-efficient gasoline vehicles for market share? The results have implications for the ZEV mandate and fuel economy policies.

3. Data

This study relies on data from a large-scale, nationally representative revealed preference survey of new car buyers. The size and scale of the survey allows for a rich, nationally representative analysis of current and potential adopters of BEVs. The dataset used is a subset of the 2013 New Vehicle Experience Survey (NVES) conducted by Strategic Vision Inc. (SV). The survey was sent out to car buyers who purchased a new vehicle from October 2012–June 2013. There were 162,701 respondents who completed at least part of the survey, but for this analysis 88,404 entries were used based on respondents who answered all the questions used in this analysis. There are six fuel types covered in the 88,404 entries used from the SV survey: gasoline, flex fuel, diesel, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs).

Our study primarily utilizes two sets of elements from the NVES data (i) consumers' reasons for purchase, (ii) their demographic characteristics. Along with the above two sets of variables, another set of variables related to geographical conditions corresponding to the state where the vehicle was purchased is also considered. A descriptive list of all the variables used in this analysis is provided in Supplementary Table 1. The NVES data also provides weights that correspond to the ratio of the number of buyers for each make and model in the national market to the number of respondents for the same make and model in the survey. Additionally, respondents in the survey are asked to state which car model they most seriously considered (but did not purchase) and to list the other vehicles owned by their household. These data were used specifically in the cannibalization section.

The *purchase reason* set of variables represents respondents' responses to the survey questions related to reasons for buying a particular vehicle. In particular, the respondents are asked a series of questions related to their reasons for purchasing the vehicle they bought, which they have to rate on a scale of 1 to 5. As an example, the respondents are asked — on a scale of 1 to 5, how important is fuel economy to your purchase decision and so on. The original Strategic Vision NVES 2013 questionnaire had 52 questions (and thus 52 variables) related to reasons for purchase. Among these 52, variables with a pairwise correlation of less than 0.6 were automatically selected for the analysis. Among groups of variables that have a pairwise correlation of more than 0.6, only one representative variable is selected.

The *demographic* set of variables corresponds to questions related to respondents' age, income and children and total other vehicles in their household. The reported age is transformed to a continuous scale to have a range from 1 to 5. The reported income is put on a logarithmic scale and then transformed to a continuous scale to have a range from 1 to 5. The *geography* variable “charging station density” is related to the electric vehicle charging infrastructure in the state where the vehicle was purchased. It is defined as the number of publicly available charging stations within the state divided by the state's urban area. In order to make it comparable to other variables, the above calculated charging station density is transformed using a logarithm function and then scaled to a range from 1 to 5. The information about number of electric charging stations within the state is obtained from the U.S. department of energy's alternative fuels and advanced vehicles website (AFDC). The data for state urban area is obtained from the U.S. census bureau website (Census.gov, 2010). The variable *winter severity* is calculated using the average winter temperature for the three winter months (December, January and February) obtained from NOAA National Centers for Environmental Information (NOAA) and is scaled to a range from 1 to 5, with the state having the lowest winter temperature having the value 5.

4. Methods

The main methodological objective of this study is to identify “potential” buyers of BEVs (those who could buy or are likely to buy in the future) via analyzing revealed preference survey data. To do that, the methodology involves two main steps: (i) segmentation of consumers into different fuel type subgroups in order to create profiles of current buyers; (ii) identification of consumers who *ex post* could be matched to a different buyer profile than the one they were originally. Step (i) is needed to create a point of reference in order for step (ii) to identify potential buyers. Once potential buyers have been identified, estimating the size of the potential market, the factors that can increase adoption, and the level of competition between fuel types can be accomplished.

4.1. Consumer segmentation

Because prior studies have demonstrated significant heterogeneity among current and potential electric vehicle buyers (Axsen et al., 2015), we allowed for the possibility of multiple BEV buyer profiles. We also allowed for the other fuel types to have multiple segments as well.

Creating different buyer profiles entails segmenting the consumers into different groups based on similarity of features. Consumers in the same group have a high degree of similarity to each other, and consumers in different groups have a high degree of dissimilarity. A flowchart describing the segmentation process is provided in Supplementary Figure 1. Briefly, we first divide consumers based on the fuel type of the vehicle they purchased. Then

we further segment the consumers within each fuel type using k-means clustering. The correlation distance metric, as shown in Eqs. (1) and (2), is used for the k-Means clustering. The Calinski–Harabasz criterion is used to determine the optimum number of clusters for each fuel type. In addition to the Calinski–Harabasz criterion, the Duda–Hart criteria was also tested, which gave similar results. In terms of initialization, multiple initialization conditions were tried and the optimum clustering results based on the Calinski–Harabasz criterion were selected.

$$\text{Distance} = 1 - \text{Correlation}(x, y) \quad (1)$$

$$\text{Correlation}(x, y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (2)$$

Once the clustering step is complete, variables separating the different fuel type clusters are identified using a stepwise multinomial logistic regression (MLR). The objective is to eliminate variables that do not have any explanatory power with regards to separating the different fuel type clusters. The different fuel type clusters are considered as the dependent categorical variables, while the variables defined in Supplementary Table 1 are considered as the set of independent variables for the stepwise-MLR. A backward elimination scheme is used for the stepwise regression. The stopping criterion for the stepwise-MLR is until all coefficients have p-values less than 0.05. Once the stopping criterion has been met, the clustering is repeated for each fuel type using the new, reduced set of variables. A subsequent stepwise-MLR is performed using the new set of fuel type clusters and this iterative (clustering)-(stepwise MLR) is performed until convergence. Convergence is achieved when no more variables are eliminated during stepwise-MLR between two consecutive iterations.

From the segmentation described above, representative buyer profiles are created using the centroid (mean) for each respective cluster. Only the variables that have a non-zero coefficient in the converged clustering-stepwise MLR for the respective fuel type clusters are considered. This representative buyer is termed as an avatar for the rest of the discussion.

4.2. Identifying potential buyers

Our assumption is that the most probable potential BEV buyers will be buyers of non-BEVs who have similar observable characteristics as current BEV buyer types along relevant parameters. It is possible that future BEV buyers may not resemble current BEV buyers. It is also possible that current non-BEV buyers that resemble current BEV buyer types may never actually purchase a BEV. However, it seems intuitive that current non-BEV buyers who resemble current BEV buyer types more than non-BEV buyer types are more likely to purchase a BEV in the future. The idea of customized marketing to likely buyers identified using either a single attribute or a combination of attributes, is also based on similar assumption (Rane et al., 2015).

It is important that potential buyers should not be identified based on *a priori* assumptions about what a BEV buyer ought to look like. Instead, potential adopters should be identified based on a non-arbitrary measure of statistical similarity. However, as the analysis comparing BEV buyers to non-buyers demonstrated, there are certain features that are more important than others in defining their profiles, e.g. valuing environmental friendliness, fuel economy, technical innovations and so on. Therefore, the criteria for measuring statistical similarity should weigh factors differently depending on their relevance, which can be accomplished by training a supervised learning model. The limitation of standard approaches to developing a supervised learning model is

that they will assign a weighting to attributes in such a way that predictions made by the model correspond as closely as possible to the actual data. In order to identify potential buyers, however, our supervised model needs to be able to systematically make predictions that are counterfactual; in that by definition potential buyers *did not* buy a BEV.

This study employs what we refer to as *ex-post* counterfactual inference in order to identify non-BEV buyers who statistically resemble the profiles of current BEV buyer types. In the standard approach to training a supervised learning model, the dataset is randomly partitioned into training and testing sets so that both are representative of the overall population. The parameters of the model are estimated on the training set and the efficacy of the model is assessed based on the predictive performance on the testing set. In *ex-post* counterfactual inference, the holdout set is not selected at random but instead comprises of members who seem in between BEV buyers and non-BEV buyers based on unweighted observable characteristics. The rest of the population is used to train the model. The holdout set with the “in-between” buyers are then given to the trained model. If the model predicts that a member in this hold-out dataset is a BEV buyer when in fact the member was a non-BEV buyer, that member is identified as a potential buyer.

There are three steps for identifying potential buyers: step (1), defining the scenario; step (2), assigning the buyer population into training and hold-out datasets; step (3) determining the probability of each buyer of belonging to different clusters, i.e. identifying potential buyers. Once steps (1)–(3) have been completed, steps (2) and (3) are repeated until convergence. A flowchart describing the process is provided in Supplementary Figure 2. A detailed description for each step is provided below.

Step 1: Defining a scenario. The first step in the potential market sizing estimation is to define a scenario. In our analysis, we defined two different scenarios, pragmatic and optimistic. The definitions of these scenarios are given in Step 2.

Step 2: Assigning buyer population to a training dataset and hold-out dataset. The entire population is separated into a training set and a hold-out dataset. Hold-out datasets are identified by fuel type cluster and then merged together to form a single hold-out dataset for the scenario. All the members that are not present within the hold-out dataset are assigned to the training dataset. A schematic diagram describing how the hold-out dataset is identified for a particular fuel type cluster is presented in Supplementary Figure 3.

Consider the process of identifying the holdout dataset for a BEV cluster, referred to as “BEV-1”. First, the distance of each BEV-1 member and the BEV-1 centroid is measured. The distance metric is defined as $1 - \text{correlation}(x, y)$, where the correlation is measured between the BEV-1 centroid’s responses (x) and a BEV-1 member’s responses (y). Let the distribution of distances between each BEV-1 member and the BEV-1 centroid be denoted by D_1 . Then the distances within which 50% and 75% of the BEV-1 population lie are measured. The corresponding distances are used to define two different cases termed as pragmatic growth case and optimistic growth case respectively. Let the distances be denoted by r_{Prag_1} , r_{Opt_1} respectively. Let us for discussion purposes consider the pragmatic growth case for BEVs. For this case, all the non-BEV members who are closer to the BEV-1 centroid than any other centroid and have a distance from the BEV-1 centroid less than r_{Prag_1} are selected for the holdout dataset.

The above steps are repeated for each avatar (fuel type cluster centroid) to identify the hold-out dataset. In any case, the hold-out dataset for the analysis is the union of the hold-out datasets identified for each fuel type centroid. For the two sets of results presented in Fig. 3 and Supplementary Figure 9, we ran two scenarios. For the first scenario, we assumed pragmatic growth

opportunity for all fuel types and for the second scenario, we assumed optimistic growth opportunity for BEVs and pragmatic growth opportunity for the remaining fuel types.

Step 3: Determining probability of each individual of belonging to each fuel type cluster. For a particular scenario, once the members going into the hold-out dataset have been identified, all the remaining members are assigned to the training dataset. By design, the members in the training dataset will be “closest” to their respective centroid. Once the data have been partitioned, the MLR model from the end of the consumer segmentation analysis is fitted on the training set. The trained MLR model is then applied on the hold-out dataset to determine the probabilities of each member of belonging to each fuel type cluster. Let P_{ijf}^H denote the probability of the i th member of belonging to the j th cluster of f th fuel type. Then, within the hold-out dataset, we reassign members to the fuel type cluster for which it has maximum probability and the fuel type for each member in the hold-out dataset is accordingly updated. For example, let us say a particular member in the hold-out dataset was originally in the Gas-2 cluster. Now, let us say its probability of belonging to BEV-3 cluster came out to be the highest. Thus, now this member will be assigned to the BEV-3 cluster and it will be assumed that this member bought a BEV fuel type.

Finally steps (2) and (3) are repeated until convergence, which is when no appreciable change occurs in the predicted market share for BEV fuel type between two consecutive iterations.

Estimating size of potential market, factors to increase adoption and fuel type competition

As mentioned in the introduction, this paper seeks to answer four main questions: (i) who buys BEVs and for what reasons, (ii) who might buy BEVs and how many of them are in the market, (iii) what factors can induce them to buy, and, (iv) to what extent are BEVs competing with other fuel types for market share? To answer question (i), we applied a Kolmogorov–Smirnov equality-of-distributions test followed by a stepwise binary logit regression comparing BEV buyers with the rest to understand the differences between the two groups. The factors separating the three different BEV buyer profiles was identified through a stepwise multinomial logit regression.

The size of the potential market in question (ii) is computed using Eq. (3).

$$MS_f = \frac{N_f^T + \sum_j \left(\sum_{i=1}^{N^H} w_i P_{ijf}^H \right)}{\left(\sum_f N_f^T + \sum_{i=1}^{N^H} w_i \right)}, \quad (3)$$

where, MS_f denotes the potential market share for f th fuel type, N_f^T represents total number of buyers of f th fuel type in the training set,

N^H represents the total number of members in the hold-out dataset

w_i represents the weight associated with each member in the hold-out dataset

P_{ijf}^H denote the probability of the i th member of belonging to the j th cluster of f th fuel type in the hold-out dataset

The barriers to adoption or factors that can induce potential BEV buyers to adopt in question (iii) are based on the differences between current and potential buyers. The comparison between each potential BEV buyer segment and the respective actual BEV buyer segment is made by carrying out a Kolmogorov–Smirnov equality-of-distributions test followed by a stepwise binary logit regression, similar to question (i). For question (iv), the fuel type that potential buyers actually purchased can be used to infer the level of cannibalization between fuel types, i.e., what percentage

of a fuel type's sales growth comes at the expense of a competitor. The cannibalization is calculated based on Eq. (4).

$$C_{fg} = \frac{MS_{f \rightarrow g}}{MS_f}, \quad (4)$$

Where, C_{fg} is the cannibalization in f fuel type's market share due to buyers switching from f fuel type to g fuel type,

$MS_{f \rightarrow g}$ represents the market share moving from f fuel type to g fuel type,

MS_f represents the actual market share for f fuel type.

5. Results and discussion

5.1. Study of current adopters

In order to understand the main characteristics of current BEV buyers, we took a statistical comparison of BEV buyers in the survey to non-BEV buyers (see Methods). The typical BEV buyer is a tech savvy, green enthusiast, who leases BEV as a second vehicle for their household, which alleviates range and resale anxiety. On the other hand, a typical non-BEV buyer prefers an aesthetically pleasing vehicle, with proven powertrain technology, robust resale value, strong towing capability and reliable handling in inclement weather. For a detailed description of the results, see the Supplementary Table 2, Supplementary Figures 4 and 5.

To account for heterogeneity among electric vehicle buyers (Axsen et al., 2015), we segmented current buyers into three optimally distinct clusters. For a schematic representation of how buyers were segmented and compared, see Fig. 1a, and please see Fig. 2 for results. Although all three BEV segments care strongly about environmental friendliness, technical innovation, and fuel economy, there were the following differences among them. BEV-1 cares mainly about owning/operating costs; BEV-2 has a higher average income and cares mainly about performance and styling; and BEV-3 values style and performance while caring strongly about costs. Thus, the BEV-3 type buyers are the most demanding of the BEV consumer segments we identified. The BEV-3 type also has a lower income than the average BEV buyer and owns fewer cars, and thus has fewer alternatives to a BEV for long-range trips. See Supplementary Table 3, Supplementary Figures 6 and 7 for detailed results.

Although the construction of consumer profiles relied only on respondents' purchase reasons, demographics and geography, the segmentation reflects BEV models actually purchased by buyers. BEV-1 purchased Nissan Leaf; BEV-2 purchased Tesla Model S; and BEV-3 also purchased Nissan Leaf (see Supplementary Figure 8). This distinction demonstrates that the clustering segmentation reflects actual consumer decisions.

Looking at the three BEV clusters from the lens of consumer adoption theory indicates that the BEV-3 Nissan Leaf buyers are representative of “early majority” type because of their high expectations from their vehicle. On the other hand, the BEV-2 Nissan Leaf buyers are much more aligned with “innovators” and “early adopters” because of their high risk tolerance as indicated by the fact that they assign very low importance to leasing terms as compared to BEV-1 and BEV-3 Leaf buyers.

6. Potential buyers: size of market and barriers to adoption

To identify potential buyers, we developed a data mining approach, *ex-post* counterfactual inference, that identifies non-BEV buyers that “statistically resemble” profiles of current BEV buyers. See Fig. 1b for a schematic of how potential buyers were identified. We ran two scenarios, (i) where we assumed a pragmatic growth opportunity for BEVs and other fuel types,

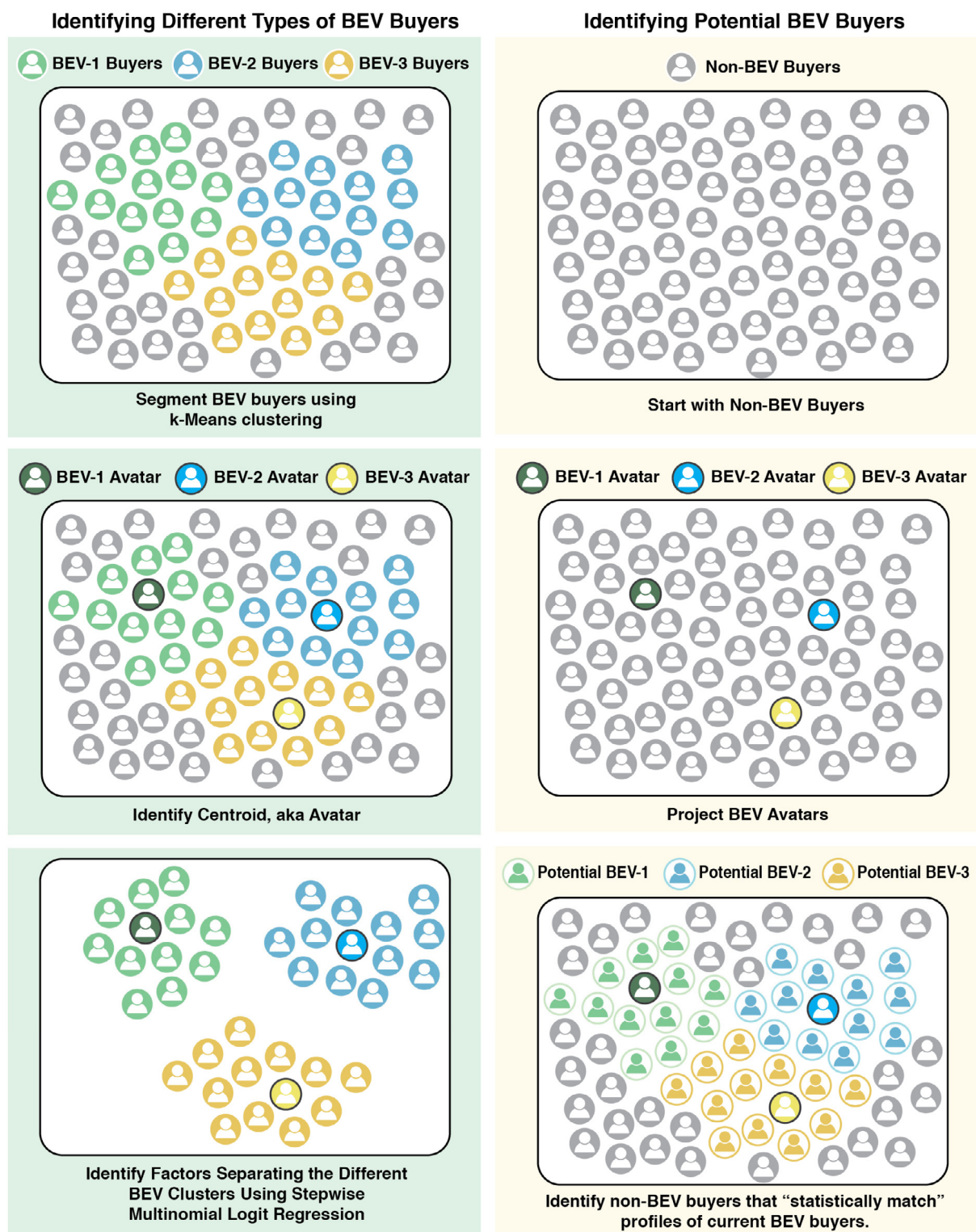


Fig. 1. Schematic diagram for (a) identifying different types of BEV buyers, (b) identifying potential BEV buyers. Please see Methods for more details.

and (ii) where we assumed an optimistic growth opportunity for BEVs and pragmatic growth opportunity for other fuel types. The conditions that define a pragmatic growth opportunity and an optimistic growth opportunity are described in the Methods section.

The potential market shares for each BEV adopter profile in the two scenarios are shown in Fig. 3. In our optimistic scenario, the BEV market has the potential to grow up to an equilibrium market

share of 2.4%, provided appropriate measures are taken. The maximum scope for growth exists in the BEV-3 segment, which, as demonstrated in the earlier sections, is the most demanding BEV buyer type segment.

To identify factors that can induce potential BEV buyers to adopt BEVs and increase market share from 0.3% (in Oct 2012–June 2013) to 2.4%, we compared actual BEV buyers to potential buyers (see Methods). For discussion purposes, we focus our

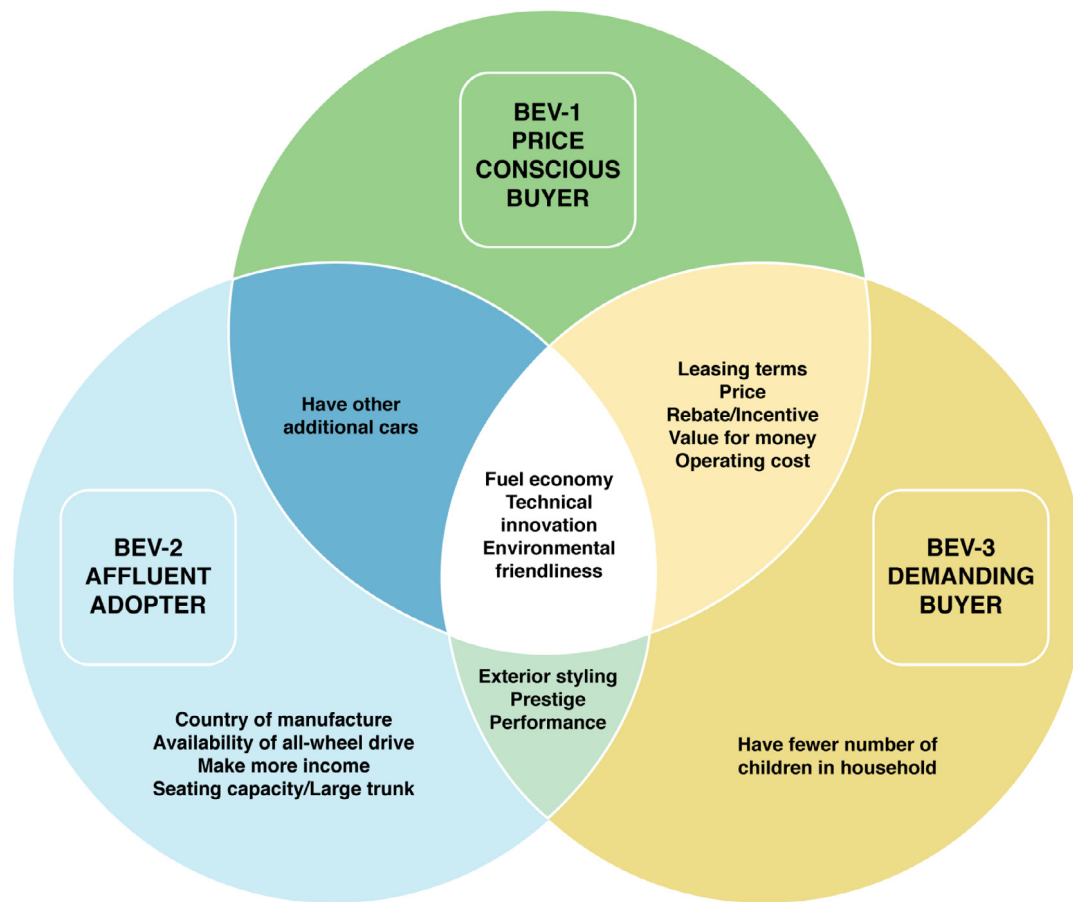


Fig. 2. A Venn diagram describing the different types of BEV buyers, highlighting the similarities and differences between them. Please see Supplementary Table 3, Supplementary Figures 6 and 7 for detailed results.

attention on BEV-3 buyers, because they have the maximum scope for growth. Fig. 4 summarizes the factors that could induce adoption amongst potential BEV-3 buyers. See supplementary Table 5 and Supplementary Figures 10–12 for a summary of the differences.

We found out that potential BEV-3 buyers are even more demanding. They care more about added features such as exterior styling and better handling in inclement weather while simultaneously being more cost-conscious. This may be because potential BEV-3 buyers own even fewer additional cars on average (see Supplementary Figure 12), and thus their new vehicle must satisfy a wider variety of needs. Having fewer alternatives for long-distance travel suggests that potential BEV-3 buyers might require longer BEV driving range than current buyers. Potential BEV-3 buyers also care less about technical innovations, suggesting that adding new technology such as automated driving will be less effective at increasing market share as compared to adding common features such as all-wheel drive for better handling.

7. Caveats — time-frame and exogenous factors

Our approach predicts an equilibrium market share, i.e., the market share that would eventually be reached provided the suggested set of measures are taken. It is an equilibrium estimate in the sense that in order to achieve market shares over and above the predicted level, factors exogenous to our current model would have to be favorably altered. The model predictions are in line with a scenario analysis, not a forecast. The timeframe within

which the predicted levels of market shares are achieved depends upon the enactment of suggested measures.

We identify two primary exogenous factors that could affect the size of the potential market for BEVs: the vehicle choice set and retail gasoline prices. Expanding the vehicle choice set available to buyers by introducing BEV models significantly different from the models available on sale during the survey period (Oct 2012–June 2013) could increase the size of the potential market. For example, the introduction of a BEV minivan or pickup truck could lead to the creation of an additional BEV buyer profile that is distinct from the profiles identified in this study. Most of the economical BEVs planned or announced in the near future such as the Chevy Bolt or Tesla Model 3 have features that would be in line with the preferences of potential BEV-3 buyers, such as higher electric driving range, better exterior styling, availability of all-wheel drive and affordable pricing. Whether or not the latest and upcoming BEV SUV/CUV (sports utility vehicle/crossover utility vehicle) models such as the Tesla Model X will appeal to significantly different buyers or whether they will appeal to the same buyers as luxury BEV sedans, such as the Tesla Model S, remains to be seen.

The gasoline price, exogenous to our model, has dropped significantly since the considered timeframe (Oct 2012–June 2013). Low gasoline prices have already seen a boom in SUV sales and a drop in sales of alternative fuel efficient vehicles including BEVs (Shepardson and Lienert, 2015). Thus, with current low gasoline prices, the optimistic scenario in our study seems even more optimistic.

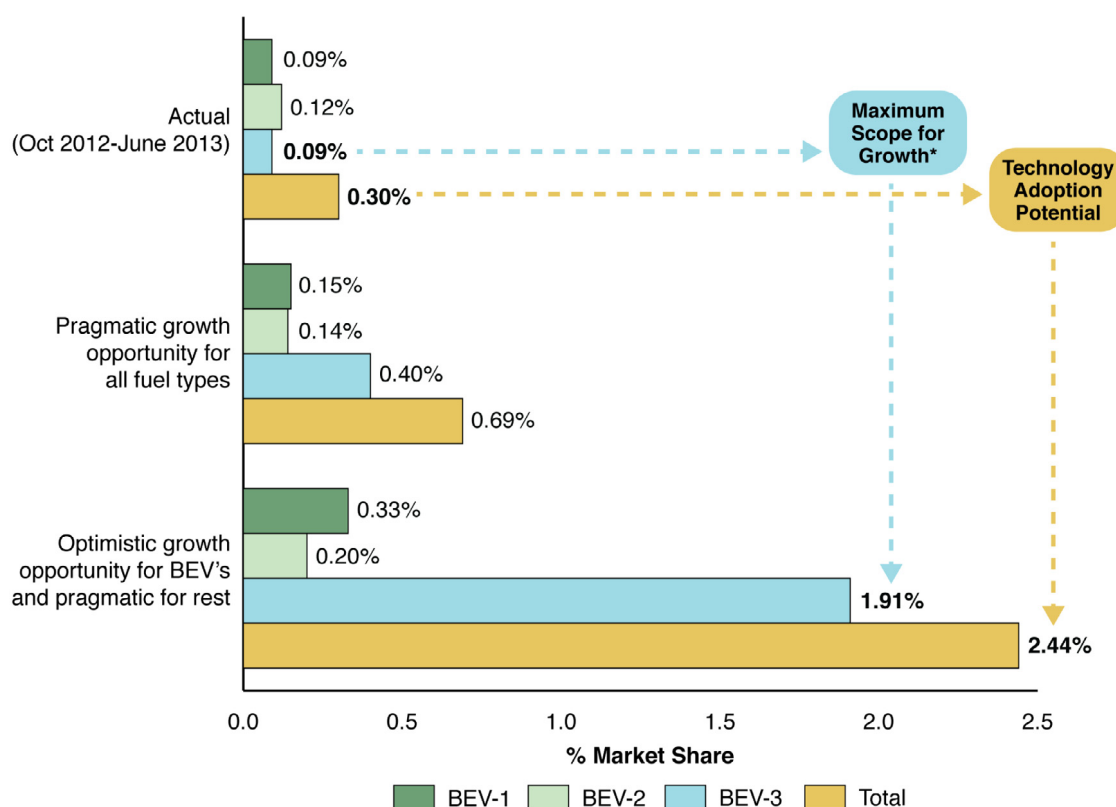


Fig. 3. Potential BEV market share for two different scenarios: (i) pragmatic growth opportunity for all fuel types, (ii) optimistic growth opportunity for BEVs and pragmatic growth opportunity for rest. For a comparison to historical BEV market shares, see Supplementary Table 4. To see specific results for California and ZEV targets, see Supplementary Figure 9.

8. Competition with other fuel types

BEV adoption does not occur in vacuum but in the context of various competing fuel technologies, many of them directly or indirectly encouraged by government policies. The federal Corporate Average Fuel Economy (CAFE) program in the U.S., which mandates improving fuel economy of LDVs over time, incentivizes the development and sale of fuel efficient internal combustion engine vehicles (ICEVs) and AFVs. The results from the potential buyer analysis can be extended to other fuel types to show the extent to which EVs (BEVs, PHEVs, hybrid electric vehicles (HEVs)) and fuel-efficient gasoline vehicles compete with each other over similar consumers. As discussed in the Methods section, identifying potential BEV adopters entails simultaneously identifying potential adopters for all fuel types represented in our survey (see data description for a list of fuel types). The fuel type that potential buyers actually purchased can be used to infer cannibalization rates between fuel types, i.e., what percentage of a product's sales growth comes at the expense of a competitor. For example, if a large portion of potential BEV buyers has currently purchased an HEV, we can infer that growth in BEV sales will cannibalize HEV sales.

In a scenario where BEV market share increases to 2.4%, total EV market share (HEV + PHEV + BEV) will overall increase from 4.06% to 5.64% (see Fig. 5, top). However, HEV and PHEV market share will decrease from current levels. This reduction in market share can partially be attributed to cannibalization from BEV sales. Among potential BEV buyers, 6.29% and 3.26% of them purchased an HEV or PHEV respectively (see Fig. 5, bottom left), resulting in cannibalization rates of 3.87% and 25.8% (see Fig. 5, bottom right). Current BEV buyers in the survey often stated that they considered purchasing an HEV (e.g. Toyota Prius) or a PHEV

(e.g. Chevy Volt) in lieu of a BEV (see Supplementary Table 6). Often, these buyers would also already owned an HEV (e.g. Toyota Prius) in their household (see Supplementary Table 7). These facts suggest that many current BEV buyers were previous HEV buyers and decided to buy a BEV in lieu of buying another hybrid (or PHEV).

Apart from competition from other EV fuel types, the highest level of competition for market share for BEVs comes from gasoline vehicles. In the scenario, gasoline buyers constitute the highest source of sales growth for all EV types (see Supplementary Figure 13). In addition, current EV buyers switching to gasoline vehicles result in double-digit sales cannibalization for all EV fuel types (see Supplementary Figure 13). Potential buyers who switched to EVs predominantly purchased fuel-efficient gasoline vehicles, such as the Honda Civic (see Table 1). Growth in EV market share, whether it came from BEVs or otherwise, would come at the expense of fuel-efficient gasoline vehicles. Alternatively, improvements in fuel-efficient gasoline vehicles would mitigate gains for EVs. Not only are all three EV types competing against fuel-efficient gasoline vehicles, but they are competing against similar models of fuel-efficient gasoline vehicles (see Table 1). For example, the Nissan Altima and the Honda Civic were commonly purchased by all three types of potential EV buyers. As HEVs, PHEVs and BEVs are also competing directly for market share with fuel-efficient gasoline vehicles, they are also competing indirectly with each other as well. A buyer that switches from a fuel efficient gasoline vehicle to a BEV is one that did not switch to a PHEV.

9. Policy implications

Under favorable conditions, the BEV market has potential to reach an annual U.S. market share of 2.4%. The key to achieving

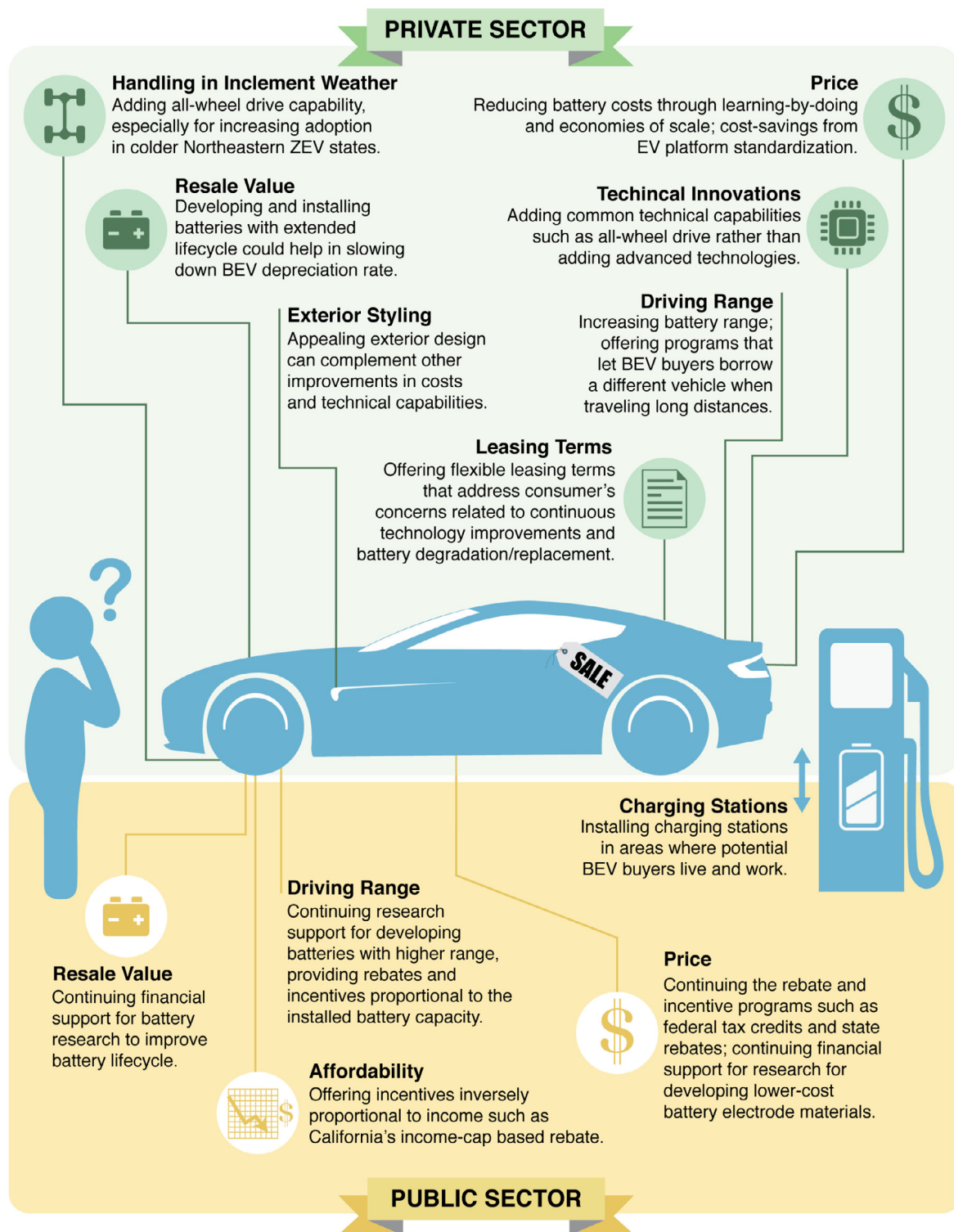


Fig. 4. Factors that can induce potential BEV-3 buyers to adopt BEVs, obtained by comparing potential BEV-3 buyers with actual BEV-3 buyers. Factors are segmented between public and private sector initiatives. For more details, please see Supplementary Table 5 and Supplementary Figure 12.

this level of growth is to target the relatively demanding potential BEV-3 buyers. To appeal to these buyers, BEVs will need to include more features such as better exterior styling, longer driving range and all-wheel drive for handling in inclement weather. Potential BEV-3 buyers also care more about price and resale value than current buyers. In short, to achieve the market share predicted in this analysis, better BEVs must be sold at lower

prices, similar to that of common compact and midsize sedans. Public subsidies and incentives are expected to be phased out as battery costs come down; however, it is important to take into account that declining battery costs will be offset by the added costs of including better features needed to attract more buyers. Decisions to remove subsidies and incentives should take these additional costs into account, rather than just battery costs alone.

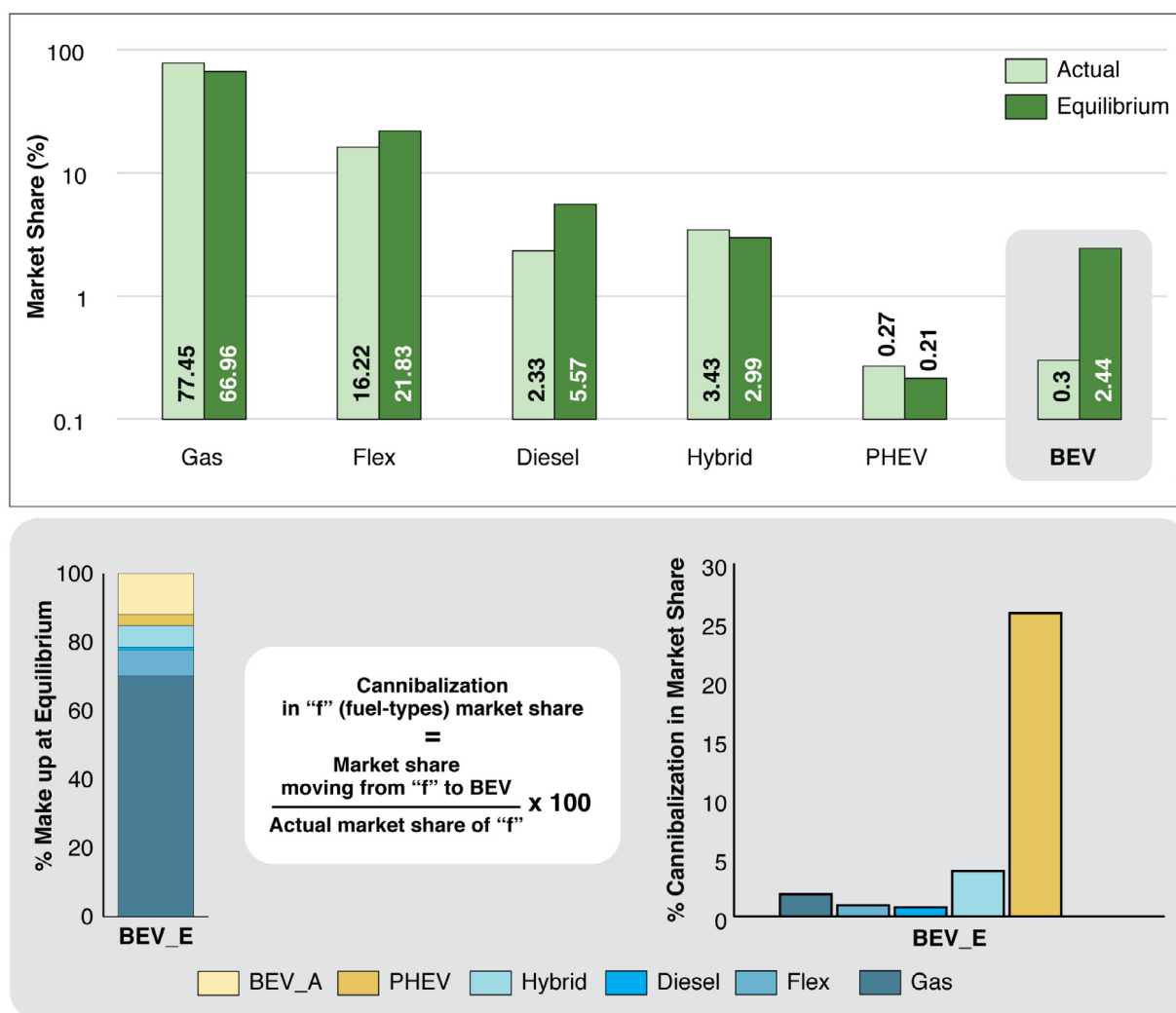


Fig. 5. (Top) Actual and equilibrium market share for different fuel types for the scenario assuming optimistic growth for BEVs and pragmatic growth for rest; (bottom-left) percent makeup at equilibrium for BEV; and (bottom-right) percent cannibalization for each fuel type due to out flux of market share from the respective fuel type to BEV. For full results, see Supplementary Figure 13.

Table 1

Top 10 models actually purchased by potential EV fuel type buyers. To see results for all potential alternative fuel type buyers, see Supplementary Table 9.

Potential HEV	Potential PHEV	Potential BEV
Volkswagen Passat	Nissan Leaf	Honda Civic Sedan
Honda Accord Sedan	Ford C-MAX	Volkswagen Jetta (Sedan)
Honda Civic Sedan	Nissan Altima Sedan	Nissan Altima Sedan
Nissan Altima Sedan	Acura RDX	Volkswagen Passat
Honda CR-V	Dodge Dart	Honda Accord Sedan
Volkswagen Jetta Sedan	Fiat 500	BMW 3 Series Sedan
Volkswagen Golf	Ford Fiesta Sedan	Nissan Sentra
Volkswagen Jetta (Wagon)	Ford Fusion	Chevrolet Volt
Volkswagen New Beetle	Honda Civic Sedan	Honda CR-V

There is also a need to consider intra-EV competition when promoting adoption. Although total EV market share can increase, promotion of BEVs could cannibalize HEVs and PHEVs. Not only do EV buyers significantly overlap, they also compete over a similar segment of fuel-economy conscious gas buyers. Efforts to promote adoption of fuel-efficient gasoline vehicles, as incentivized by the Federal CAFE standards, may reduce the growth of BEV adoption. CAFE and ZEV are not necessarily mutually exclusive though because BEV sales count favorably towards CAFE standards because of their high fuel efficiency and low

emissions (EPA/NHTSA, 2012). However, fulfilling CAFE standards through sales of fuel-efficient gasoline vehicle sales does not count towards fulfilling ZEV regulation.

Two primary exogenous factors that could affect the size of the potential market for BEVs beyond what is estimated in this study include the vehicle choice set and retail gasoline prices. Expanding the vehicle choice set available to buyers by introducing BEV models significantly different from the models available on sale during the survey period (Oct 2012–June 2013) could increase the size of the potential market. On the other hand, low gasoline prices could result in a drop in sales of alternative fuel efficient vehicles including BEVs.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.egy.2019.04.013>.

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