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Designing policy incentives for cleaner technologies: Lessons from California's plug-in electric vehicle rebate program

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ABSTRACT

We assess the performance of alternative rebate designs for plug-in electric vehicles. Based on an innovative vehicle choice model, we simulate the performance of rebate designs that vary in terms of vehicle technologies, consumer income eligibility, and caps on the price of vehicles eligible for subsidies. We compare these alternatives in terms of 1) the number of additional plug-in electric vehicles purchased, 2) cost-effectiveness per additional vehicle purchase induced, 3) total program cost, and 4) the distribution of rebate funding across consumer income classes. Using the status quo rebate policy in California as a reference case, we identify two alternative types of designs that are superior along all four performance criteria.

Introduction

Policymakers design public incentives with the aim of inducing consumers to adopt innovative technologies that reduce environmental damages. Such incentives may include price subsidies, rebates, tax credits, sales tax exemptions, and subsidized financing. These policy incentives are currently deployed to induce consumers to adopt technologies such as alternative fuels and vehicles, energy and water efficient technologies, and renewable energy technologies, among others. While the critique of these incentives as "second best" from a social efficiency perspective is well known, researchers have paid much less attention to how to cost-effectively and equitably design these commonly encountered policy incentives.

We use California's plug-in electric vehicle (PEV) rebate program as a reference case in order to explore the opportunity for both more cost-effective and equitable policy deigns. In our policy setting, there are several possible sources of heterogeneity that the incentive policy's design might leverage. First, the policy may set different rebate levels for different products, in our case for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). Second, a policy may employ price caps, which would make PEVs above the specified price ineligible for a rebate. Third, a policy could base rebate levels on heterogeneity. Recently California adopted legislation (SB 1271) requiring rebate levels to vary with consumers' income levels and subsequently announced it would limit rebates to households with incomes under $500,000 (or

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individuals with incomes under $250,000).

We motivate our empirical analysis with a theoretappeical model of a social planner who must determine the rebate level to assign to consumers in order to maximize PEV purchases subject to a budget constraint. Our social planner faces heterogeneous consumers in their ex ante utilities for the new products and their marginal utilities of income. Our model predicts that the social planner's optimal rebate to assign decreases as a consumer's ex ante value of the product increases. Consumer segments with high ex ante values for the product are more likely to purchase the product under any policy, thus qualifying in greater numbers for the rebate than are consumer segments with lower ex ante product values. As a result, targeting consumers with lower ex ante values is more cost-effective, requiring less public rebate revenue for the same change in consumer probabilities of product switching. Second, our model predicts that the social planner's optimal rebate increases as the consumer's own marginal utility of income increases. Any given rebate level is more effective in maximizing the sum of probabilities of purchasing the product for the segment of consumers who are relatively more price responsive.

Our fundamental contribution is an approach to simulating the cost-effectiveness of alternative policy designs. The relevant policy setting is one in which policymakers must set incentives levels across more than one product and for which consumers have product-differentiated demands. The basic elements of the analysis require that the researcher has estimates of 1) the price elasticities of demand for the relevant dimension of consumer heterogeneity (i.e., income classes in our case), 2) the distributions of consumers' willingness to pay for each product, and 3) prices for the products. The researcher can then explore through demand simulations how the assignments of financial incentives across products and consumer segments will affect the number of total additional products purchased, the total cost of policy (e.g., required public revenues), and the cost effectiveness per additional product purchased. We also illustrate the use of a simple metric for comparing allocative equity across policy designs.

In order to evaluate the effects of a variety of rebate designs, we first develop and estimate an innovative empirical model of consumer vehicle choice. The centerpiece of our empirical analysis is a consumer vehicle choice model that enables us to model the consumer choices across all makes and models currently in the California market. A statewide representative survey of 1261 prospective new car buyers in California enables us to identify individual preferences for conventional and alternative vehicle technology attributes, allowing us to estimate price elasticities of demand and willingness to pay for different vehicles. We integrate this data on vehicle sales and market structure to predict the effect of alternative rebate policy designs on our policy performance metrics.

We then use this model to simulate the performance of rebate designs. We find that the status quo policy is effective, increasing the market share of PEVs by at least 7%. The status quo policy offers $1500 and $2500 rebate for PHEVs and BEVs, respectively. We find that the incidence of free riding by consumers who would have purchased PEVs in the absence of a rebate means that policy cost per *induced* PEV purchase is around $30,000 for the status quo policy.

Our initial simulation of alternative policy designs explores the effects of changing rebate levels across the two vehicle technologies (BEVs and PHEVs). These simulations reveal the impacts of consumers' differing ex ante values (i.e., willingness to pay) for BEVs and PHEVs on the performance of rebate policies. For example, allocating higher rebates to BEVs, for which consumers have a relatively lower value, reduces the number of total additional PEVs sold but also improves policy cost-effectiveness and lowers total policy costs. While some policymakers give BEVs relatively higher rebates because they believe BEVs produce relatively higher social benefits, our recommendation that BEVs receive relatively higher rebates compared to PHEVs is based solely upon a cost-effectiveness criteria.

Our second set of analyses explores the effects of vehicle price caps. A vehicle price cap policy excludes PEV adopters from a rebate who have relatively higher values for PEVs as expressed by their willingness to pay more for the PEV. Because relatively higher-income consumers tend to have relatively higher willingness to pay for PEVs, a vehicle price cap may render many higher-income PEV adopters ineligible for the rebate. Evaluating a vehicle price cap of $60,000, we find that 10% fewer additional vehicles are sold, while cost-effectiveness improves and total program costs fall by 34%. However, we find that vehicle price caps do not appear to significantly improve the allocative equity as some policymakers have suggested they would. For the California market context, this appears to be true for two reasons. First, many higher-income consumers also purchase lower-priced PEVs. Second, a vehicle price cap does not influence how rebates to vehicles below the price cap are allocated across consumers of different incomes.

Our third set of analyses evaluates redesigning the existing rebate program to give consumers in lower-income classes relatively higher rebates. Rebate policy designs that are progressive with respect to income reduce the number of consumers who receive rebates, but who would have purchased the PEVs anyway. These policies also target lower-income consumers who have a higher marginal value for the rebate and who are less likely to purchase a PEV except in the presence of higher rebate levels. We find that these policies increase the number of additional PEVs sold per rebate dollar spent (i.e., the cost-effectiveness of the policy) relative to the status quo policy.

Overall, we find two types of policy designs are superior to California's status quo policy along performance dimensions. The first type of policy offers very progressive rebate levels based on consumer income levels. An example of this policy would offer consumers purchasing BEVs who make incomes of 1) less than $25,000, a rebate of $7500, 2) $25,000–$50,000, a rebate of $5000, 3) $50,000–$75,000, a rebate of $2000, and 4) over $75,000, no rebate. Consumers purchasing a PHEV in these same income categories would receive $4500, $3000, and $1000, respectively. The second type of policy combines a less progressive rebate schedule with a vehicle price cap. An example of this policy would implement a $60,000 vehicle price cap above which no rebate is offered while offering consumers making less than $100,000 a rebate of $5000 for BEVs and $3000 for PHEVs. These policies sell at least as many PEVs over the next three years as the status quo policy, are more cost effective (e.g., PEV sold per dollar spent), have lower total policy costs, and result in a significantly greater allocative equity.

Literature on design of technology adoption policies

Our central thesis is that a fiscal policy could be improved by recognizing and leveraging heterogeneity among consumers. This idea first emerged in the modern economics literature with the discussion of design of tax policies (Diamond, 1970). However, this insight has not been widely developed and applied to the emerging literature on the design of incentives for innovative technology adoption policies. Instead, researchers concerned with technology adoption policies have to sought understand the types of externalities that may arise and how to best internalize these through our choice of policy instrument.

Researchers have evaluated whether PEV adoption will lead to emissions decreases or increases (Babaee et al., 2014). More sophisticated analyses have linked increased electricity demand by PEVs with spatially explicit changes in emissions and air pollution exposures (Graff Zivin et al., 2014; Holland et al., 2015). Researchers have also evaluated the effectiveness, measured in terms of health outcomes, of alternative transportation policies and technologies associated with hybrids and PEVs (Michalek et al., 2011; Congressional Budget Office, 2012; Tessum et al., 2014). Researchers have argued that there may exist a distinct set of externalities around innovation, adoption, and diffusion of new technologies that goes beyond the standard health, safety, and environmental externalities that have motivated public regulations traditionally. The majority of these externalities take the form of sub-optimal knowledge spillovers among either consumers (i.e., learning by using) or producers (i.e., learning by doing) (e.g., Jaffe et al., 2002, 2005; Fischer and Newell, 2008; Bollinger and Gillingham, 2012). In the context of emerging innovative product markets, early adopters may face large private (learning) costs while producing large social (learning) benefits for later adopters leading to knowledge spillovers and adoption rates that are socially sub-optimal. Policies for innovative technologies with these externalities, these authors would argue, ought be designed to achieve the socially optimal schedule of knowledge spillovers in addition to internalizing environmental or health externalities (Jaffe et al., 2005).

A large literature exists that evaluates optimal choice of policy instruments for these externalities (Gillingham et al., 2006). Tax and cap and trade policies establish *both* positive incentives for the adoption and use of relatively cleaner technologies *as well as* negative incentives for the adoption and use of relatively more polluting technologies. In contrast, policies such as rebates, tax credits, sales tax exemptions, and similar subsidies only establish positive incentives for the adoption and use of relatively cleaner technologies and thus are called "second best" policies. In the context of transportation policies, feebate policies have sought to replicate the effects of a tax policy by increasing the price of relatively more polluting vehicles while reducing the price of less polluting vehicles. Policy analyses of feebate policies often share our analytical approach of using estimates of consumers' price elasticity of demand to evaluate changes in market share of the targeted vehicles.

Advocates of incentive policies often point to studies of demand for cleaner alternative vehicles which show that consumers have lower demand for, and less knowledge of, these vehicles than other internal combustion engine vehicles (Bunch et al., 1993; Brownstone et al., 2000; Axsen and Kurani, 2009; Hidrue et al., 2011). Historically, three types of vehicle incentive policies have been evaluated by researchers: the aforementioned feebate policies, as well as hybrid-electric vehicle (e.g., Diamond, 2009; Chandra et al., 2010; Beresteanu and Li, 2011; Jenn et al., 2013; Sierzchula et al., 2014), and "cash-for-clunkers" policies (e.g., Huang, 2010; Gayer and Parker, 2013; Li et al., 2013; Mian and Sufi). We compare our estimated effects of the California Vehicle Rebate Program on changes in market share with these studies in Section 4.

An issue related to policy instrument choice that has recently received attention is that consumers appear to respond differently to financial incentives of different types, but which convey the same net value to consumers (Chetty et al., 2009). Researchers have shown that consumers respond more to rebates and sales tax exemptions that occur nearer to the point of sale than to income tax incentives, which must be applied for and received at some later point in time. Gallagher and Muehlegger (2011) provide an example for cleaner vehicle technologies when they report that Hybrid Electric Vehicle sales increase more in response to sale tax exemptions that to income tax credits/exceptions.

How much of a vehicle incentive is actually transferred to consumers depends upon its economic incidence. Incidence analysis anticipates that manufacturers or dealers will have an incentive to strategically adjust a vehicle's price in response to the presence of vehicle incentives. Whether market conditions permit this type of value appropriation will depend upon the relative elasticities of supply and demand curves for the vehicles.[3] The available empirical evidence on the incidence for advanced clean vehicles comes from analyses of hybrid vehicle tax incentives. Examining the Toyota Prius, Sallee (2011) finds that drivers capture nearly all of the available tax incentives. Busse et al. (2006), who examine the incidence of dealer versus manufacturer controlled incentives, find a range between.31 and.81 cents on each dollar goes to the buyer depending upon the type of incentive. In the context of our analyses, as long as the rebate incidence is equal across all vehicles, our

[3] In market settings where the price elasticity of demand is lower than the price elasticity of supply, dealers will receive a disproportionate share of incentives, making such an appropriation through price adjustments possible. When the price elasticity of demand is higher than the price elasticity of supply, such a price adjustment becomes less possible in a competitive market.

findings remain valid although the overall effectiveness of the rebate (on consumer purchases) would go down if dealerships capture some of rebates' value.

Theoretical model

Suppose there is one PEV available on the new car market and J non-PEVs available for consumers to choose from. To incentivize PEV adoption, a social planner offers rebates to I consumers who purchase PEVs. A utility-maximizing individual will purchase a vehicle when her utility from doing so exceeds her utility from purchasing any other available vehicle as well as the her utility from the outside option not to purchase a vehicle. We focus on the decision to purchase a new PEV, contingent upon having chosen to purchase a new vehicle.

Contingent upon having decided to purchase a new vehicle, an individual purchases a PEV when her total utility from the decision, $u_{i,PEV}$, is greater than her utility for purchasing any other vehicle, $u_{i,j}$.[4] Let total utility for the PEV be her ex ante value for the PEV, v_i, minus the cost of the PEV, p, times her marginal utility of income, β_i.

The social planner reduces PEV price for consumers by assigning rebates, r_i, out of a policy budget, $\mathfrak{R}$, such that

$$u_{i,PEV} = v_i - \beta_i(p - r_i). \tag{1}$$

The policy maker's objective is to maximize the sum of individual new car buyer probabilities of purchasing PEVs, $\pi_i = prob(u_{i,PEV} > u_{i,j})\ \forall\, j \neq PEV$, by allocating the rebates cost effectively subject to the government's budget constraint:[5]

$$\max_{\{r_i\}} \sum_i prob(u_{i,PEV} > u_{i,j})\ \forall\, j \neq PEV \tag{2}$$

$$S.\,T.\ \sum_i \mathbb{E}[\pi_i r_i] \le \mathfrak{R}. \tag{3}$$

Assuming utilities are linear and the sources of actionable difference between consumers are observable, we can model probability as a conditional logit model:

$$\max_{\{r_i\}} \sum_i \frac{\exp(u_{i,PEV})}{\sum_k \exp(u_{i,k})} \equiv \max_{\{r_i\}} \sum_i \frac{\exp(v_i - \beta_i(p - r_i))}{\exp(v_i - \beta_i(p - r_i)) + \sum_j \exp(u_{i,j})}\ \forall\, j \neq PEV. \tag{4}$$

The choice variable is the rebate level, r_i, which only affects utility of the PEV and not the utility of other vehicles.[6] The social planner cannot affect the utility of the other vehicles ($u_{i,j}$ for $j \neq PEV$). Therefore, in this framework, maximizing the sum of the probabilities of choosing the PEV is equivalent to maximizing the sum of the utilities for the PEV:[7]

$$\begin{aligned} &\max_{\{r_i\}} \sum_i \left[v_i - \beta_i(p - r_i) \right] \\ &S.\,T.\ \sum_i \mathbb{E}[\pi_i r_i] \le \mathfrak{R}. \end{aligned} \tag{5}$$

Solving the constrained maximization problem above results in the following first order condition, where λ is the shadow value of the budget constraint:

$$\lambda = \frac{\beta_i}{\pi(r_i) + \beta_i \pi(r_i) r_i - \beta_i \pi(r_i)^2 r_i}. \tag{6}$$

If there are N new car buyers, then there are N first order conditions similar to Eq. (6), one for each car buyer. We can solve these first order conditions for λ and set them equal to each other. The stylized case where $N=2$ is instructive because it can help illustrate the influences of varying the characteristics of two different consumers. In this case, we find the following:

$$\lambda = \frac{\beta_1}{\pi(r_1) + \beta_1 \pi(r_1) r_1 - \beta_1 \pi(r_1)^2 r_1} = \frac{\beta_2}{\pi(r_2) + \beta_2 \pi(r_2) r_2 - \beta_2 \pi(r_2)^2 r_2}. \tag{7}$$

[4] For simplicity, we assume there is only one available PEV. The intuition from the theoretical model holds when there are multiple PEV models available.

[5] Note the objective function to maximize PEV purchases given the social planner's budget is not a standard welfare maximization problem. Many states have already decided to promote the adoption of PEVs. Given this decision, the objective function is representative of a policy maker's goal to increase PEV adoption cost-effectively.

[6] We assume the consumer fully captures the rebate and ignore potential supply-side responses such as manufacturer and dealer pricing decisions.

[7] Note that the denominator from Eq. (4) does not fall out, but rather, since $\sum_j \exp(u_{i,j})$ remains constant, maximizing Eq. (4) is equivalent to maximizing the numerator of Eq. (4). In other words, maximizing x is equivalent to maximizing $\frac{x}{x+C}$ where x is a choice variable and C is a positive constant.

As shown in the online appendix, under the assumption that $\pi_i < \frac{1}{2}$, we find the following comparative statics:[8]
Optimal rebate decreases as own ex ante value increases:

$$\frac{\partial r_1}{\partial v_1} < 0. \tag{8}$$

Optimal rebate increases as other's ex ante value increases (via the interaction of the shadow price for consumers 1 and 2 in Eq. (7)):

$$\frac{\partial r_1}{\partial v_2} > 0. \tag{9}$$

Optimal rebate increases as own marginal utility of income increases (i.e., more price sensitive):

$$\frac{\partial r_1}{\partial \beta_1} > 0. \tag{10}$$

Optimal rebate decreases as other's marginal utility of income increases (via the interaction of the shadow price for consumers 1 and 2 in Eq. (7)):

$$\frac{\partial r_1}{\partial \beta_2} < 0. \tag{11}$$

These comparative statics show that higher rebates should be assigned to consumers with higher marginal utility of income and/or lower ex ante value for PEVs. The intuition for this result is shown in Fig. 1. Probability of purchasing the PEV is proportional to utility for the PEV. As shown in Fig. 1a, we can plot utility of the PEV versus rebate level as a linear function where the y-intercept is utility without the rebate, $v_i - \beta_i p$, and the slope of the function is the marginal utility of income, β_i. Although probability of purchasing the PEV increases with r_i, there is positive probability that the consumer will purchase the PEV in the absence of the rebate. If the consumer purchases the PEV in the absence of the rebate, the purchase is non-marginal in the sense that the purchase was not induced by the rebate policy. Area A is a proxy for the non-marginal purchase probability. Area B is a proxy for the marginal purchase probability; that is, by how much the rebate increases the probability of the consumer purchasing a PEV. The higher the consumer's ex ante value for the PEV, the higher her non-marginal purchase probability. The higher the consumer's marginal utility of income, the more responsive she will be to the rebate, and the higher her marginal purchase probability. The comparative statics show us that rebates are more cost effective when they target consumers with a higher ratio of marginal to non-marginal purchase probability, i.e., lower ex ante values and higher marginal utilities of income.

Fig. 1b shows that if two consumers have the same probability of purchasing the PEV in the absence of the rebate, the policy maker should target the rebate towards consumer 1, who has the higher marginal utility of income and thus has a higher ratio of marginal to non-marginal purchase probability. Fig. 1c shows that if two consumers have the same marginal utility of income, the policy maker should target the rebate towards consumer 2, who has the lower ex ante value and thus has a higher ratio of marginal to non-marginal purchase probability. In Fig. 1d consumer 1 has a higher ex ante value for the PEV and a higher marginal utility of income, whereas consumer 2 has a lower ex ante value and a lower marginal utility of income. In this case the policy maker would want to assign rebates r_1 and r_2 such that the ratio of consumer 1's marginal purchase probability to non-marginal purchase probability equals that of consumer 2, as proscribed by Eq. (7).

We can also think about Fig. 1 as a demand curve, since PEV utility on the y-axis is proportional to quantity demanded and rebate on the x-axis is a measure of price. Therefore, our theoretical results suggest that rebates should be targeted towards consumer segments with lower market share and steeper demand curves. Targeting consumer segments and/or products with lower market share is cost effective because it results in fewer rebates being allocated to infra-marginal purchases. Targeting consumer segments and/or products with steeper demand curves is more cost effective because the rebates stimulate more marginal purchases.

3.1. Cost-effectiveness analysis of rebate designs across two technologies

In our empirical analysis, we limit ourselves to a cost-effectiveness analysis of alternative rebate designs rather than evaluating the socially optimal rebate design. We do not know the marginal social benefits (e.g., avoided externalities) associated with PEV purchases that would be needed to define a social optimum. However, the social planner's problem above makes several predictions (e.g., Eqs. (8)–(11)) about how to improve the cost-effectiveness of rebate policy designs with information readily available to the economists' standard demand analyses.

We adapt and apply this model prediction to an empirical and simulation setting in order to increase the number of PEVs

[8] Given the market share of PEVs, the probability of the average consumer purchasing a PEV is likely to be considerably less than 50%, so the assumption that $\pi_i < \frac{1}{2}$ seems reasonable.The intuition of this condition is that once a consumer's probability of purchasing the PEV is high enough, her optimal rebate goes to zero and remains at zero if her ex ante value v_i or marginal utility of income β_i change marginally. This implies that if a consumer is going to purchase a PEV regardless, then it is a "waste" of public resources to give this person a rebate regardless if she is rich or poor.

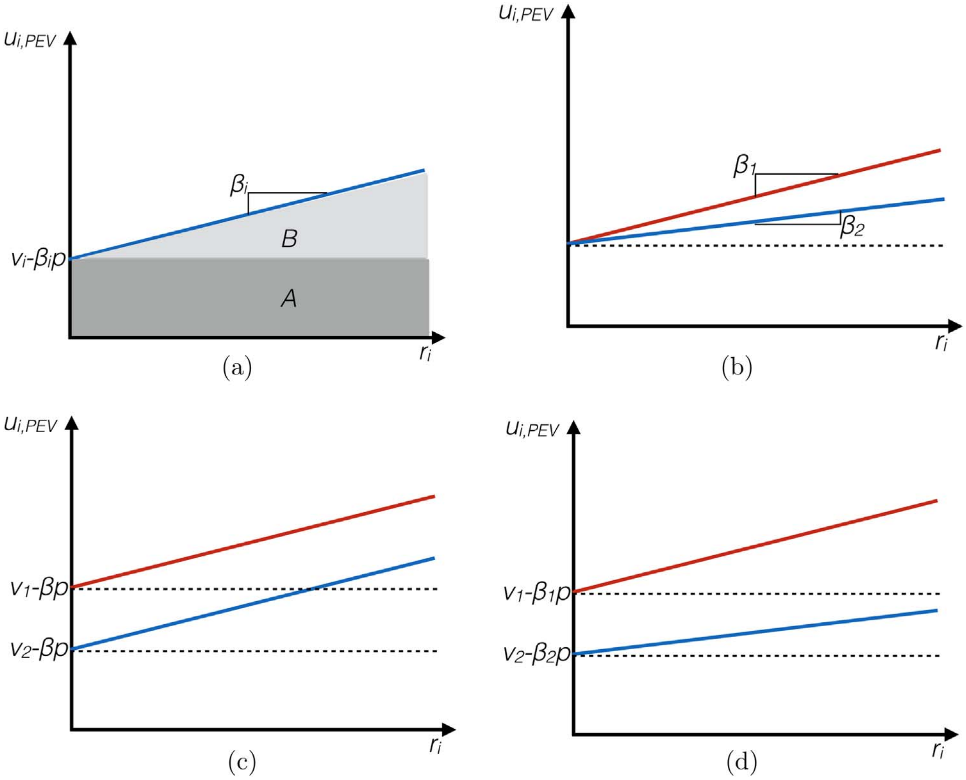


Fig. 1. Marginal versus Non-Marginal PEV purchase probability.

sold per public dollar spent (i.e., cost-effectiveness). We consider the policy problem of setting rebate levels for two types of PEVs, BEVs and PHEVs, for which consumers have very different ex ante values. We find that the consumers' ex ante values are lower for BEVs than PHEVs. From Eq. (8), we predict that if rebate levels are relatively higher for BEVs as compared to PHEVs then the policy will be relatively more cost-effective. We also consider the policy problem of setting rebate levels when the marginal utility of income varies across consumer (e.g., income) classes. We find that lower-income classes have a higher marginal utility of income than do higher-income classes. Eq. (10) suggests that relatively higher rebate levels for relatively lower income classes will produce more cost-effective policy outcomes.

3.2. Welfare maximization

Assessing the design of a vehicle purchase rebate from the perspective of maximization welfare highlights several challenges that cost effectiveness analysis circumvent. First, vehicle purchase incentives are “second best” instruments compared to “first best” cap and trade or tax instruments. This is because although these incentives alter consumers' vehicle purchase decisions they cannot influence consumers' decisions about how much to drive a vehicle. As a result this incentive cannot precisely target externalities that arise in proportion to the vehicle miles traveled such as local air pollution and state-wide greenhouse gas emissions. A second complication for vehicle incentives is that the social planner may be trying to target different externalities at once. In California these include suboptimal knowledge spillovers across both drivers and automakers, locally-varying air pollutant damages, and state-wide greenhouse gas damages. This multiplicity of externalities also makes setting the welfare-maximizing level of a vehicle incentive very challenging.

3.3. Model extensions

One extension of this model would consider the inter-temporal dynamics of consumer-to-consumer information spillovers. In the context of emerging innovative product markets, early adopters may face large private (learning) costs while producing large social (learning) benefits for later adopters, leading to knowledge spillovers and adoption rates that are socially sub-optimal (Stoneman and Diederen, 1994).[9] Model extensions that target incentives to consumers in social networks with larger spillovers could further improve the cost effectiveness of rebate assignment.

Importantly, our theoretical recommendation to increase the relative rebate levels for relatively lower demand and lower

[9] For a more detailed discussion see Jaffe, Newell, and Stavins, 2002, 2005; Fischer and Newell, 2008; Bollinger and Gillingham, 2012.

market share goods assumes that product quality is comparable across the goods. We do not consider product quality differentiation within the model, which might be one cause for relatively lower demand and market share (Heutel and Muehlegger, 2015). In the dynamic setting described in the previous paragraph, product quality would be an important consideration, as subsidization of low quality products may lead to negative network spillovers (e.g., bad reviews).

A second extension would recognize potential supply-side responses that rebate incentives might induce. Specifically, incentive levels may change manufacturers' decisions regarding pricing, production volumes, manufacturer and dealer incentives, marketing campaigns and even new product offerings. While modeling the supply side is beyond the scope of this paper, some of these supply-side influences do depend upon a more accurate understanding of rebate-induced consumer behavior which we aim to provide here.

Empirical model and simulations

4.1. Empirical model

The probability of a new car buyer selecting vehicle k (i.e., the market share of vehicle k) can be described as the new car buyer population-weighted average of the probabilities of new car buyers selecting vehicle k:

$$prob(V_k) = \frac{\sum_{i=0}^{N} w_i prob_i(V_k)}{\sum_{i=0}^{N} w_i}, \tag{12}$$

where
$prob(V_k)$: Average probability of purchasing vehicle k
$prob_i(V_k)$: Probability of individual i purchasing vehicle k
w_i: Weight on individual i needed to make the sample representative of the new car buying population.

The probability of individual i selecting vehicle k is the product of the probability of individual i purchasing a vehicle, the probability of individual i selecting a new vehicle over a used vehicle contingent upon having chosen to purchase a vehicle, the probability of individual i selecting the make of vehicle k out of all available makes, the probability of individual i selecting the body type of vehicle k out of all available body types, and the probability of individual i choosing vehicle k over all other vehicles of the same make and body type:

$$prob_i(V_k) = prob_i(Vehicle)prob_i(New\ Vehicle|Vehicle)prob_i(M_k)prob_i(B_k)prob_i(V_k|M_k, B_k), \tag{13}$$

where
M_k: Make of vehicle k
B_k: Body type of vehicle k.

Our survey focuses on individuals who have already decided to purchase a new vehicle. We model the decision to purchase a PEV contingent upon having decided to purchase a new vehicle:[10]

$$prob_i(V_k|New\ Vehicle) = prob_i(M_k)prob_i(B_k)prob_i(V_k|M_k, B_k). \tag{14}$$

Assuming linear utility with standard Type 1 extreme value errors, we can model each probability component as a conditional logit:

$$prob_i(B_k) = \frac{\exp(v_{1i}(B_k))}{\sum_{j=0}^{N} \exp(v_{1i}(B_j))} \tag{15}$$

$$prob_i(M_k) = \frac{\exp(v_{2i}(M_k))}{\sum_{j=0}^{N} \exp(v_{2i}(M_j))} \tag{16}$$

$$prob_i(V_k|M_k, B_k) = \frac{\exp(v_{3i}(V_k|M_k, B_k))}{\sum_{j=0}^{N} \exp(v_{3i}(V_j|M_j, B_j))}, \tag{17}$$

[10] If we had a representative sample of the general population, as opposed to a representative sample of new car buyers, then we could estimate the initial decision to purchase a new vehicle versus a used vehicle or no vehicle. The advantage of focusing on new car buyers is that we obtain a much richer data set on decisions to purchase PEVs. This truncated model assumes that all households planning to purchase a new vehicle follow through with their decision, and that no households not planning to purchase a new vehicle change their minds. There are a few potential violations of this assumption. There may be households who intend to purchase a new vehicle but do not because their current vehicle lasts longer than expected or due to adverse financial shocks. There may be households who were screened out of our sample due to their stated intention not to purchase a new vehicle who nevertheless purchase a new vehicle. Lastly, our sample excludes households who are not planning to purchase a new vehicle, but who may be induced by the PEV rebate policy to purchase a new vehicle.

where
v_{1i}, v_{2i}, and v_{3i}: Linear utility functions of individual i.

In order to make it tractable, the empirical model is somewhat restrictive. Our main assumptions include 1) limited vehicle substitution patterns,[11] 2) full capture of the rebate by consumers (Sallee, 2011), and 3) that the introduction of the rebates does not induce more new vehicle purchases but rather shifts some conventional new vehicle purchases to PEV purchases.

4.2. Data

We administered an online survey to a representative sample of Californian new car buyers[12] and obtained a sample of 1261 completed surveys. Of the respondents who completed an initial screener, approximately 42% both qualified as potential new car buyers and completed the survey.

There are several advantages to using stated preference data in this study. PEV sales account for a very small share of the new vehicle market, and until recently, only a few models were widely available. Available revealed preference data, such as vehicle registrations, do not include consumer characteristics. With stated preference data we are able to relate consumer preferences to observable heterogeneity, which is necessary to target rebates toward different consumer segments.

Since we vary prices randomly according to an experimental design, we avoid common endogeneity problems associated with estimating demand as a function of prices. Using stated preference data also allows us to assume a richer set of PEVs by estimating preferences for PEVs that did not exist at the time the survey was administered but have become commercially available since then or are likely to in the near future.

The survey first gathered household, vehicle, and demographic data. Next, the survey elicited body and brand preferences. Respondents were asked to choose the top two vehicle body types (out of twelve options) they were most likely to select for their next new vehicle purchase.[13] Then respondents were asked to select the top three brands (out of the twenty most popular brands by sales volume in California in 2012) they were most likely to select for their next new vehicle purchase.

Next, respondents were shown four sets of five vehicles, as shown in Fig. 2, and in each set were asked to choose which of the five vehicles they were most likely to select for their next new vehicle purchase. The total set of twenty vehicles respondents chose from included all conventional vehicles (including internal combustion engine vehicles, hybrid electric vehicles, and diesel-fueled vehicles) on the new vehicle market as of the fall of 2013 that are of both the top brand and top body selected by respondents. The remainder of the twenty included a random draw of vehicles that are of the top body choice and second or third brand choice, or of the second body choice and top brand choice. In cases where the set of vehicles that meets these criteria is less than twenty, the remainder of the vehicles were a random selection of vehicles that are of either of the top body selections or of the top brand selections. Finally, respondents were asked to choose which one of the four vehicles chosen as top picks out of the twenty vehicles in the previous four questions they would be most likely to select for their next new vehicle purchase, as shown in Fig. 3. This 'top' vehicle and its characteristics are carried through to subsequent questions in the survey.[14]

Respondents were provided with information on BEV and PHEV technologies and introduced to PEV attributes, including refuel price, electric range, and HOV lane access. Finally, respondents were asked to choose between the conventional version, two BEV versions, and two PHEV versions of the vehicle they previously indicated as their top choice.[15] In each choice set the first column displayed the conventional vehicle, and we randomized whether the two BEVs or PHEVs appeared in the subsequent columns. Attribute levels vary for each vehicle version as shown in Table 1, with price pivoting off the price of the existing conventional vehicle. An example choice set is shown in Fig. 4. By choosing between five versions of the top vehicle, *respondents are encouraged to assume that everything else (e.g., trim and performance) except the listed attributes are identical*. This allows us to focus on how respondents make tradeoffs between vehicle technology, price, refuel cost, electric range, and HOV lane access.

To make the choice experiment more realistic for respondents, we employ a pivot design. Price levels are designed to be

[11] This assumption is discussed in Section 4.5.

[12] A survey sample large enough to obtain the same level of detail on both the initial decision to purchase a new vehicle as well as on PEV tradeoffs would have been far outside the budget constraint for this project.

[13] The survey focuses on decisions respondents make regarding their next new vehicle purchase, regardless if the next new vehicle is a primary or non-primary household vehicle. Although there is evidence that households with more vehicles are more likely to diversify household vehicle fleets with PEVs (Kurani et al., 1996), by focusing on purchases that are likely to happen in the next few years, we are better able to estimate PEV sales over a medium-term policy period. Furthermore, our simulations account for heterogeneity in preferences across income groups, which likely reflects not only differential marginal utilities of income but also differential ex ante preferences that may be driven in part by household vehicle fleet.

[14] The purpose of selecting a top conventional vehicle is twofold. First, it allows the respondent to self-identify with the subspace of the large new vehicle market that she is most likely to purchase from in the future. This is important because PEV availability is currently constrained to a subset of brands and body types (mostly small sedans and hatchbacks). Second, we pivot off the top vehicle in the subsequent choice experiment, meaning that respondents choose between conventional, BEV, and PHEV versions of their top vehicles, and price of the alternatives is a function of the price of the respondent's top vehicle. This results in respondents facing more realistic choices.

[15] Depending on a respondent's top vehicle choice, the BEVs and PHEVs presented in the choice experiment may or may not be actual vehicles available on the market. The choice experiments assume maximal penetration by offering PEV versions of all vehicle models. The survey was administered during a time where new PEV models were rapidly becoming available on the market.

If the set of vehicles to choose from were those in the table below, what would your choice be?

For QC:
'MercedesBenzcompactsedan2','Nissancompactsedan1','AudicompactSUV5','MitsubishicompactSUV1','VolkswagencompactSUV

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Brand and Model	Mercedes Benz C-Class Sedan	Nissan Sentra Sedan	Audi SQ5 SUV	Mitsubishi Outlander Sport SUV	Volkswagen Tiguan SUV
Refueling cost (per mile)	$0.18	$0.15	$0.20	$0.17	$0.22
Purchase price	$35,350	$15,990	$51,900	$19,470	$22,995
Select your first choice	○	○	○	○	○

Next

Fig. 2. New car buyer survey: top vehicle choice.

Here are the vehicles you selected earlier as your top choices. From these, please pick your overall first choice and second choice of vehicle that you would be most likely to purchase if you were purchasing a new vehicle now.

For QC: 'Fordcompactsedan2','Hondacompactsedan1','Nissancompactsedan1','ToyotacompactSUV1'

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Brand and Model	Ford Focus Sedan	Honda Civic Sedan	Nissan Sentra Sedan	Toyota RAV4 SUV
Refueling cost (per mile)	$0.15	$0.14	$0.15	$0.17
Purchase price	$16,310	$18,165	$15,990	$23,300
Select your first choice	○	○	○	◉
Select your second choice	○	◉	○	○

Next

Fig. 3. New car buyer survey: top vehicle choice.

percentages of a reference value. The price of the top conventional vehicle chosen by a respondent becomes her reference price, and the different price levels she sees are the percentage levels as specified by the experimental design multiplied by the reference price. For example, a respondent who selects a conventional model that costs $30,000 would see BEV and PHEV versions of that model that cost $31,500, $34,500, $37,500, or $45,000. On the other hand, a respondent who is considering the luxury end of the market and selects a conventional model that costs $60,000 would see BEV and PHEV versions of that model that cost $63,000, $69,000, $75,000, or $90,000.

The conventional vehicle prices are therefore taken as fixed and we vary the PEV prices around that. As a result, we do not observe how consumers respond if we increase or decrease all vehicle prices but rather identify PEV demand elasticities relative to the prices of base models. However, this anchoring on current prices makes for a more realistic choice experiment.

More details of the experimental design are given in Sheldon et al. (2016). The experimental design excludes dominated choices, such that a vehicle with better attribute levels (greater range, lower refueling cost, etc.) is more expensive. However, attributes are not perfectly correlated with price. For a given price point, the other attribute levels vary randomly subject to non-domination of the alternative.

4.3. Comparison of data and results to revealed preference

In order to validate the new car buyer survey data, we cross-check the respondent characteristics with a sample of new car buyers from the Caltrans 2010–2012 California Household Travel Survey (California Department of Transportation, 2013).

Table 1
Attribute levels.

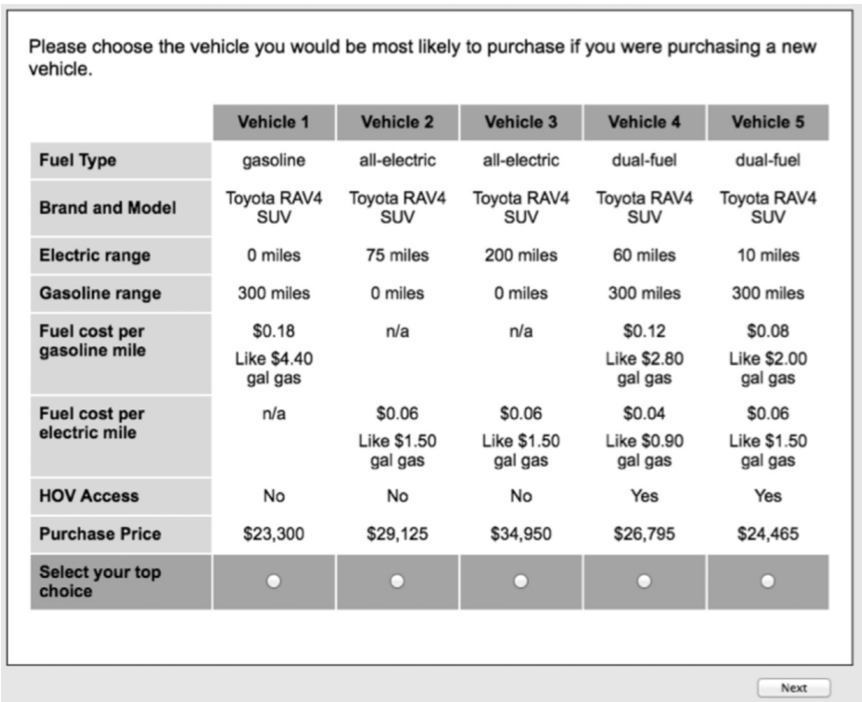
Purchase price[a] (**% of conventional**)	
Gasoline	100%
BEV	105%, 115%, 125%, 150%
PHEV	105%, 115%, 125%, 150%
Gasoline refuel cost (**$ per gal**)	
Gasoline[b]	$4.00, $4.40, $4.80, $5.60
BEV	n/a
PHEV[c]	$2.00, $2.20, $2.40, $2.80
Electric refuel cost[d] (**$ per gal equivalent**)	
Gasoline	n/a
BEV	$0.90, $1.10, $1.50, $2.50
PHEV	$0.90, $1.10, $1.50, $2.50
Gasoline range (**miles**)	
Gasoline	300
BEV	300
PHEV	0
Electric range (**miles**)	
Gasoline	n/a
BEV	50, 75, 100, 200
PHEV	10, 20, 40, 60
HOV Access	
Gasoline	no
BEV	no, yes
PHEV	no, yes

[a] The respondent sees price in dollars. For example, a respondent who selected a conventional model that costs $30,000 would see BEV and PHEV versions of that model that cost $31,500, $34,500, $37,500, or $45,000.

[b] At the time the survey was administered, average gasoline cost in California was approximately $4 per gallon.

[c] The average gasoline fuel economy of PHEVs as of December 2013 was 41 mpg, which is roughly double the fuel economy of our gasoline vehicle universe of 20 mpg. Therefore we choose a baseline gasoline refueling cost for PHEVs that is half that of gasoline vehicles.

[d] At the time the survey was administered, the average overnight electricity rate in California was roughly 16 cents per kWh and the average vehicle economy of electric vehicles was 3.5 miles per kWh, suggesting an average cost per electric mile of $0.046. The average cost per mile of gasoline vehicles in our vehicle universe is $\frac{\$4/gal}{20mi/gal} = \$0.20$ per mile. Thus on average, refueling cost for electric miles is 23% of the $4 per gallon refueling cost for gasoline miles, or $0.92/gal. Therefore we choose a baseline electric refueling cost of $0.90 per gallon equivalent.


Please choose the vehicle you would be most likely to purchase if you were purchasing a new vehicle.

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Fuel Type	gasoline	all-electric	all-electric	dual-fuel	dual-fuel
Brand and Model	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV
Electric range	0 miles	75 miles	200 miles	60 miles	10 miles
Gasoline range	300 miles	0 miles	0 miles	300 miles	300 miles
Fuel cost per gasoline mile	$0.18 Like $4.40 gal gas	n/a	n/a	$0.12 Like $2.80 gal gas	$0.08 Like $2.00 gal gas
Fuel cost per electric mile	n/a	$0.06 Like $1.50 gal gas	$0.06 Like $1.50 gal gas	$0.04 Like $0.90 gal gas	$0.06 Like $1.50 gal gas
HOV Access	No	No	No	Yes	Yes
Purchase Price	$23,300	$29,125	$34,950	$26,795	$24,465
Select your top choice					

Next

Fig. 4. New car buyer survey: PEV vs. conventional vehicle choice module.

Table 2
UCLA new car buyer survey population[a].

	Caltrans Survey, Full Population, Weighted Population	Caltrans Survey, New Car Buyers, Weighted Population	UCLA New Car Buyer Survey, Weighted Population
Household size			
1 person	24.5%	16.3%	13.2%
2 people	30.0%	30.2%	33.5%
3 people	16.4%	18.7%	19.8%
More than or equal to 4 people	29.1%	34.9%	33.4%
Number of household vehicles			
None	8.0%	3.7%	2.8%
1	32.7%	26.3%	29.6%
2	37.2%	42.9%	42.3%
More than or equal to 3 vehicles	22.0%	27.2%	25.3%
Ethnicity			
White	68.7%	75%	75.3%
African American	4.4%	4%	6.5%
Multi-Racial	7.1%	3%	1.5%
Other	19.8%	18.6%	16.8%
Household ownership			
Own	72.2%	76.8%	62.0%
Rent	27.6%	23.0%	35.0%
Other	0.1%	0.0%	2.9%
Income			
<10 k	5.6%	2.9%	5.1%
10–25 k	16.2%	9.8%	7.6%
25–35 k	10.4%	7.4%	7.7%
35–50 k	13.6%	11.7%	9.4%
50–75 k	15.9%	16.1%	16.9%
75–100 k	12.8%	15.2%	22.5%
100–150 k	11.9%	16.1%	18.8%
>150 k	13.6%	21.0%	12.1%
Drivers in household			
None	4.9%	1.6%	0.3%
1	30.9%	23.2%	19.4%
2	45.2%	50.9%	51.1%
3	13.9%	17.4%	16.3%
More than or equal to 4 drivers	5.2%	6.8%	6.8%
Sex			
Male	48.2%	49.1%	51.3%
Female	51.8%	50.7%	48.5%
Age			
Under 18	24.2%	0.1%	0.0%
18–24	10.2%	2.0%	16.2%
25–54	38.5%	50.8%	58.0%
55–64	10.7%	27.7%	14.0%
65 or over	16.5%	19.4%	10.2%
Employment			
Employed	54.0%	66.7%	63.3%
Unemployed	46.0%	32.9%	36.7%
Household type			
Single family, detached	69.2%	74.9%	64.9%

Table 2 (*continued*)

	Caltrans Survey, Full Population, Weighted Population	Caltrans Survey, New Car Buyers, Weighted Population	UCLA New Car Buyer Survey, Weighted Population
Single family, attached	7.8%	7.3%	9.9%
Mobile Home	3.3%	1.9%	2.6%
Building with 2 or more apartments	19.5%	15.7%	22.2%
Boat, RV, Van, etc.	0.0%	0.0%	0.2%
Education			
Not a high school graduate, 12 grade or less	7.4%	3.4%	7.1%
High school graduate	14.8%	11.0%	24.7%
Some college credit but no degree	18.7%	18.1%	23.2%
Associate or technical school degree	11.4%	11.0%	10.6%
Bachelor's or undergraduate degree	26.2%	30.4%	21.0%
Graduate or professional degree	21.4%	26.0%	13.2%
Vehicle body type			
Sedan	47.7%	46.3%	42.2%
SUV	18.0%	19.9%	28.3%
Truck	11.5%	10.5%	3.1%
Coupe	6.5%	6.2%	6.4%
Convertible	1.2%	1.4%	9.8%
Hatchback	3.6%	3.7%	5.6%
Wagon	3.1%	3.3%	2.3%
Minivan or Van	8.3%	8.7%	2.2%

[a] Compared to Caltrans (2013) California 2010-2012 household travel survey.

These comparisons, shown in Table 2, reveal that for 12 diagnostic variables our survey sample is very similar to the actual new car buying population. Income, education and age are included in Table 2, exhibiting modest differences for a few value categories.[16]

Also shown in Table 2 is a comparison of our estimated vehicle class share with the Caltrans 2010-2012 California Household Travel Survey (California Department of Transportation, 2013). Our estimated vehicle class shares are similar to actual market shares. The main discrepancies are pickup trucks, minivans, SUVs, and convertibles. As our survey was administered up to three years after the Caltrans survey, the lower estimates of truck and minivan shares may represent the increasing popularity of SUVs for families. The higher estimated convertible share likely represents initial desire over eventual practicality.

We compare our estimated vehicle brand shares with the actual market shares from the California New Car Dealer Association's California Auto Outlook from the fourth quarter of 2013 (California New Car Dealers Association, 2013) in Table 3. Overall, our estimated brand shares are similar to actual market shares. We also find that higher income households are more likely to select luxury brands.

Under the current rebate policy, our simulations estimate a PEV market share of 3.1%. The actual California PEV market share in the fourth quarter of 2013 was 2.5% (California New Car Dealers Association, 2013). At the time of the survey, new PEV models were rapidly coming to market. Some of the models available in December of 2013 may not have been available earlier in the fourth quarter. Additionally, consumers may not have had full information about all of the newly available PEVs. This likely accounts for the difference between our estimated market share and the actual market share. Our estimated PEV market share is close to the actual market share, which supports the predictive validity of our model.[17] In the simulations, if we use the revealed preference brand and body shares from the Caltrans survey and the California New Car Dealer Association, we estimate a PEV market share of 3.0%. If we aggregate body types to two categories, lightweight trucks and

[16] The weighted California Household Travel Survey, relative to our weighted sample, exhibits modestly fewer upper middle households ($75–100 k; 15% compared to 23%) and greater upper income households (>$150 K; 21% compared to 12%). With respect to age, it exhibits a lower number of 18–24 year olds (2% compared to 16%), modestly greater 55–64 years olds (28% compared to 14%) and greater 65+ year olds (19% compared to 10%). With respect to education, it contains fewer households with less than a high school diploma (3% compared to 7%), fewer with a high school degree (11% compared to 25%) and greater with graduated degrees (26% compared to 13%). Finally, with respect to home ownership, it has modestly greater households that own their homes (77% compared to 62%).

[17] Strategic behavior on behalf of respondents would most likely take the form of not choosing PEVs unless there was a large rebate, which would lead to an under-estimate of PEV market share.

Table 3
Estimation results: brand choice.

	Actual CA market share	Weighted survey share	Probability of purchase as estimated by a rank-ordered logit						
			All incomes	Income under $25 k	Income $25–$50 k	Income $50–$75 k	Income $75–$100 k	Income $100–$175 k	Income over $175 k
Acura	1.4%	3.0%	2.7%	2.7%	2.2%	3.3%	2.3%	2.6%	4.2%
Audi	1.7%	3.8%	3.2%	4.7%	1.1%	2.8%	3.0%	2.8%	9.4%
BMW	4.0%	5.0%	4.5%	3.1%	3.1%	3.6%	4.1%	6.3%	8.4%
Buick	0.5%	1.7%	1.3%	1.9%	0.5%	1.3%	0.3%	2.6%	1.8%
Cadillac	0.8%	1.4%	1.1%	1.5%	0.6%	2.4%	0.7%	0.8%	1.3%
Chevrolet	7.4%	9.0%	8.8%	7.4%	9.7%	8.8%	11.1%	7.6%	4.9%
Chrysler	0.6%	1.6%	1.2%	2.1%	1.7%	0.6%	0.9%	1.4%	0.5%
Dodge	2.2%	2.7%	2.7%	5.7%	3.3%	2.7%	2.3%	1.2%	2.4%
Fiat	0.5%	0.7%	1.0%	3.3%	0.4%	0.2%	0.5%	1.3%	0.0%
Ford	10.8%	10.8%	10.9%	10.8%	9.5%	10.0%	12.5%	12.3%	6.5%
GMC	1.4%	1.7%	1.6%	3.0%	3.1%	0.9%	0.7%	1.2%	0.8%
Honda	12.1%	15.2%	15.4%	16.9%	15.5%	17.4%	17.1%	12.2%	12.5%
Hyundai	3.9%	2.9%	3.3%	1.9%	5.0%	3.7%	2.2%	4.1%	1.7%
Infiniti	0.9%	1.2%	1.1%	1.1%	1.0%	0.6%	2.1%	0.9%	0.1%
Jaguar	0.2%	0.1%	0.4%	0.4%	0.1%	0.0%	0.3%	0.9%	0.2%
Jeep	1.9%	1.6%	1.7%	2.2%	2.1%	2.3%	1.1%	1.5%	1.3%
Kia	3.4%	1.7%	2.0%	2.8%	2.5%	1.9%	1.5%	1.9%	0.5%
LandRover	0.5%	0.6%	0.8%	0.1%	1.2%	1.4%	0.8%	0.5%	1.0%
Lexus	3.2%	3.1%	3.4%	1.2%	4.7%	2.9%	2.9%	3.9%	6.2%
Lincoln	0.3%	0.5%	0.8%	1.8%	0.0%	0.2%	0.7%	1.3%	0.8%
Mazda	2.2%	1.5%	1.3%	0.7%	2.3%	0.6%	0.6%	2.0%	1.1%
Mercedes	3.2%	2.2%	2.0%	0.3%	2.0%	1.6%	1.7%	2.7%	4.0%
MINI	0.8%	0.6%	0.5%	0.3%	0.2%	0.7%	0.2%	1.2%	0.3%
Mitsubishi	0.4%	0.2%	0.6%	0.6%	0.8%	1.4%	0.5%	0.0%	0.0%
Nissan	7.5%	4.2%	4.6%	3.9%	5.1%	5.7%	4.8%	4.0%	2.8%
Porsche	0.6%	0.2%	0.4%	0.2%	0.1%	0.6%	0.3%	0.3%	1.5%
Scion	1.0%	0.8%	1.2%	2.8%	0.5%	1.5%	1.8%	0.3%	0.7%
Smart	1.0%								
Subaru	2.5%	2.6%	2.2%	1.4%	3.1%	1.3%	1.3%	2.4%	5.7%
Tesla	0.5%	0.6%							
Toyota	17.5%	15.8%	16.4%	12.5%	16.2%	17.3%	17.9%	16.2%	16.7%
Volkswagen	3.4%	2.0%	2.1%	1.7%	2.1%	1.0%	2.9%	2.7%	1.2%
Volvo	0.4%	0.9%	0.9%	0.9%	0.5%	1.4%	0.7%	0.8%	1.5%

cars, we estimate a PEV market share of 3.3%.

Lastly, we relate our estimated price and income parameters to those found in the literature. A critical finding of our simulations is that as consumers' incomes rise their price elasticities decline, causing them to be less responsive to a given rebate. Similar patterns have been documented using revealed preference data in both the general vehicle market (Bunch and Mahmassani, 2009) as well as the hybrid market (Beresteanu and Li, 2011).

Using estimated quantities demanded for each vehicle across each income class before and after the rebate, we estimate an average price elasticity demand for BEVs of -1.8 and for PHEVs of -2.3. Excluding the top income class, which behaves somewhat differently, we estimate an average income elasticity of demand of 0.2 for BEVs and -0.1 for PHEVs, which reflects the relatively higher rates of BEV purchasers in the top income classes.[18] Our models yield price and income elasticities for only BEVs and PHEVs, while most estimates in the literature are for conventional new vehicles. Nonetheless, these estimated price elasticities are in line with new vehicles price elasticity estimates of -1.63 from Hess (1977) and -1.7 to -3.4 from Bordley (1993) but larger than the -0.87 estimated by McCarthy (2006). Our model yields an estimated income elasticity of 0.2 to -0.1 for BEVs and PHEVs, respectively. By comparison, Hess (1977) estimated 0.26 for new vehicles while McCarthy (2006) estimated 0.85.

4.4. Simulations

We predict PEV sales as follows:

1. Estimate $prob_i(M_k)$ *for each income class* using a rank-ordered logit. Predicted probabilities from this estimation are shown

[18] Generally speaking the price elasticity declines as household income increases, suggesting that wealthier households become relatively less price responsive. However, as income categories rise from $100k-175k to over $175k (our top income bracket), we estimate that households price elasticities rise from -0.039 to -0.089. We cannot fully explain this jump, except to speculate that it is correlated with a discontinuity of household preferences for luxury PEV.

Table 4
Estimation results: body choice.

Variable	Estimated coefficient
Compact Sedan	1.662*** (0.108)
Midsize Sedan	1.690*** (0.108)
Full-size Sedan	1.028*** (0.111)
Compact SUV	1.455*** (0.110)
Midsize SUV	1.295*** (0.112)
Full-size SUV	0.667*** (0.118)
Van or Minivan	−0.497*** (0.163)
Hatchback	0.616*** (0.126)
Wagon	−0.394** (0.157)
Compact *Number Children	-0.201*** (0.049)
Midsize*Number Children	-0.171*** (0.051)
Sportscar*Number Vehicles	0.248*** (0.030)
Observations	28,959

Standard errors in parentheses. * $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

in Table 3.

2. Estimate $prob_i(B_k)$ using a conditional logit. Covariates include body-specific constants and interactions with number of children and number of cars in a household. The estimation results are shown in Table 4. Predicted probabilities of purchasing different body types are different for individuals with different numbers of children and household vehicles. Table 5 shows the average probabilities across the sample.
3. Estimate $prob_i(V_k|M_k, B_k)$ using a conditional logit. Covariates include purchase price (MSRP), refueling cost, electric range, BEV and PHEV constants, and an indicator for single-occupant HOV lane access. The estimation results are shown in Table 6.
4. Using the representative sample of new car buyers from the survey and the characteristics of existing conventional and PEVs on the market,[19] predict PEV purchase probabilities for each individual in the sample according to Eq. (14).[20] Integrate PEV purchase probabilities over the weighted sample of new car buyers.

[19] The PEVs on the market as of fall 2013 and their characteristics are shown in Fig. A1 in the Appendix.

[20] We assume that the number of annual new vehicle purchases is constant at 2013 levels for a three year policy period and estimate the number of these purchases that are PEVs. This is reflective of our theoretical and empirical models being contingent upon the decision to purchase a new vehicle.

Table 5
Estimation results: body choice.

Body Type	Average probability
Compact Sedan	15.2%
Midsize Sedan	16.0%
Full-size Sedan	9.5%
Compact SUV	12.8%
Midsize SUV	11.1%
Full-size SUV	6.8%
Wagon	2.4%
Hatchback	5.7%
Coupe	7.5%
Van or Minivan	2.2%
Truck	3.5%
Convertible	7.3%

5. Reduce PEV purchase prices by specified rebate amount and redo step 4 to predict probabilities of purchasing existing PEVs given the different levels of rebates.

4.5. Substitution possibilities in the model

Each individual has a probability of purchasing each vehicle. The probability of an individual purchasing a Volt is the probability of her choosing a Chevrolet times the probability of her choosing a compact sedan times the probability of her choosing the Volt over alternative Chevrolet compact sedans.

The probability of choosing each brand is estimated using a rank ordered logit and is only a function of household income since almost all of the brands offer a range of body types. The implicit substitution pattern across brands is proportionate according to the standard independence of irrelevant alternatives assumption. However, because all brands are assumed to be available, there is effectively no induced substitution across brands.

The probability of choosing each body type is estimated using a conditional logit as a function of respondents' top body picks and household demographics and using the model to predict the probabilities for each individual. Individuals' probabilities can change, but only as a function of household demographics (i.e., number of children and number of household vehicles). Therefore, in this model there is effectively no induced substitution across bodies as a function of vehicle price.

However, even if an individual's most preferred body type is a compact sedan, her probability of purchasing a RAV4 BEV (an SUV) will still change as the rebate for the RAV4 BEV increases, since the individual has a full set of probabilities and the rebate increases the individual's probability of purchasing a RAV4 BEV over other Toyota SUVs. Effectively, the model assumes that a rebate on a PEV in a given class impacts an individual's probability of purchasing that PEV versus other vehicles in that class, but does not impact the individual's probability of purchasing a vehicle in the given class.

The implied substitution patterns of the model suggest that increasing PEV sales of a certain model cannibalizes sales of the auto maker's other models. For example, suppose that a respondent's top choice vehicle is a Toyota Camry and her second choice is a Honda Accord. A Toyota Camry PEV offering in our model would reduce probability of purchasing the conventional Camry and not affect the probability of purchasing the Honda Accord. To avoid this issue would require a dramatically longer survey to estimate probabilities of switching from one make-model to another make-model (e.g., from the Camry to the Accord) when a PEV is only offered for one of the two make-models. If the empirical model allowed for such substitution patterns, the simulations would predict higher PEV sales.

4.6. Other sources of demand heterogeneity

In our simulations, we find that the higher income groups purchase PEVs at higher rates (note that the simulation results presented later in the paper show total PEV sales predicted by income group, but the income groups are of different sizes). We also find by interacting the PEV indicator in the conditional logit model with various demographics that households with more than one vehicle and households that live closer to the coast are more likely to purchase a PEV, although these findings are not statistically significant.[21] These findings are consistent with characteristics of PEV purchasers over the last few years.

We currently accommodate heterogeneity in demand for PEVs by vehicle technology (BEVs, PHEVs and ICEs), body size and types, as well as some household characteristics such as income, number of children, number of pre-existing vehicles in household fleet. In related work (Sheldon et al. (2016)), we explore a number of other sources of preference heterogeneity,

[21] Although respondents were instructed to assume that residential charging would be provided with the purchase of a PEV, some respondents might have updated this to reflect increased installation costs for multi-family housing relative to single-family housing. For our sample, we find no difference in PEV purchase probabilities between households that live in single, detached houses and those who do not.

Table 6
Estimation results: vehicle choice.

Variable	Estimated Coefficient
Vehicle Price * Income Under \$25k	−0.075*** (0.028)
Vehicle Price * Income \$25–50 k	−0.062*** (0.023)
Vehicle Price * Income \$50–75 k	−0.048*** (0.016)
Vehicle Price * Income \$75–100 k	−0.054*** (0.018)
Vehicle Price * Income \$100–175 k	−0.038*** (0.014)
Vehicle Price * Income Over \$175 k	−0.089*** (0.025)
BEV * SedanHatchback	−1.989*** (0.205)
BEV * SUV	−2.090*** (0.250)
BEV * Sportcar	−2.208*** (0.278)
BEV * VanTruck	−1.687*** (0.336)
PHEV	−0.333** (0.167)
Range	0.009*** (0.001)
Refuel	−0.038 (0.041)
HOV	0.261*** (0.058)
Observations	24,940

Robust standard errors in parentheses. *$p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

and associated consumer segmentation that are not directly germane to questions of rebate policy design. The factors include vehicle range, cost per mile driven, gasoline costs, commuting patterns, access to High Occupancy Vehicle lanes, work place charging opportunities as well as household age, education, housing type, and political attitudes.

4.7. State level plug-in electric vehicle policies

Currently, several states offer financial incentives that reduce the purchase price for PEVs through direct rebate, tax credit, and sales tax exemptions. Table 7 shows the incentives offered by these states. The amount of incentive PEV buyers

Table 7
State level incentives.

State	CA	CO	GA	IL	LA
Incentive type	Rebate	Tax credit	Tax credit	Rebate	Tax credit
Maximum amount for PHEV	$1500	$6000.00	$0.00	$4000.00	$3000.00
Maximum amount for BEV	$2500	$6000.00	$5000.00	$4000.00	$3000.00
Maximum amount for a Chevrolet Volt ($35,170 for a 2015 model, 17.1 kwh)	$1500	$4731.57	$0.00	$3517.00	$3000.00
Maximum amount for a Nissan LEAF ($29,010 for 2015 model, 24 kwh)	$2500	$5162.40	$5802.00	$2901.00	$2901.00
How is it determined?	Fixed, by fuel type	A formula of purchase price (deducting federal tax credit) times battery capacity in kWh then divided by 100	20% of purchase price or $5000, whichever is less	10% of MSRP, up to $4000 for eligible models	10% of the vehicle purchase price, or $3000, whichever is less

State	MD	MA	NJ	PA	SC
Incentive type	Tax credit	Rebate	Sales tax exemption	Rebate	Tax credit
Maximum amount for PHEV	$3000	$2500.00	N/A	$2000.00	$2000.00
Maximum amount for BEV	$3000	$2500.00	N/A	$2000.00	$0.00
Maximum amount for a Chevrolet Volt ($35,170 for a 2015 model, 17.1 kwh)	$2138	$2500.00	$0.00	$2000.00	$2000.00
Maximum amount for a Nissan LEAF ($29,010 for 2015 model, 24 kwh)	$3000	$2500.00	$2030.70	$2000.00	$0.00
How is it determined?	$125 per kWh battery capacity	Fixed, by battery capacity	Zero-emission vehicles	By battery capacity (PHEVs with battery capacity less than 10 kwh receives $1000	Base tax credit is $667 for a car that has 4 kwh batteries. Each add'tl kwh receives another $111.

State	TX	UT	WA	WV
Incentive type	Rebate	Tax credit	Sales tax exemption	Tax credit
Maximum amount for PHEV	$2500	$605.00	N/A	$7500.00
Maximum amount for BEV	$2500	$605.00	N/A	$7500.00
Maximum amount for a Chevrolet Volt ($35,170 for a 2015 model, 17.1 kwh)	$2500	$605.00	$0.00	$7500.00
Maximum amount for a Nissan LEAF ($29,010 for 2015 model, 24 kwh)	$2500	$605.00	$87.03	$7500.00
How is it determined?	Fixed for eligible models	Fixed	Vehicles that run exclusively on electricity, natural gas, propane and other alternative fuels	35% against purchase price up to $7500

Table 8
PEVs sold by type of policy.

Policy	Income	BEV Rebate	PHEV Rebate	Baseline BEVs Sold	Baseline PHEVs Sold	Addt'l BEVs Sold	Addt'l PHEVs Sold	Additional PEVs Sold	Total PEVs Sold
Status Quo Policy	Under $25 k	$2500	$1500	2899	6203	473	719	9699	158,335
	$25–$50 k	$2500	$1500	6065	18,191	775	1278		
	$50–$75 k	$2500	$1500	10,313	18,667	664	963		
	$75–$100 k	$2500	$1500	6349	16,981	645	1001		
	$100–$175 k	$2500	$1500	19,822	35,735	985	1250		
	Over $175 k	$2500	$1500	4060	3371	557	389		
Policy 1: Equaling rebates	Under $25 k	$2000	$2000	2899	6203	373	805	10,602	159,258
	$25–$50 k	$2000	$2000	6065	18,191	614	1716		
	$50–$75 k	$2000	$2000	10,313	18,667	528	1290		
	$75–$100 k	$2000	$2000	6349	16,981	512	1342		
	$100–$175 k	$2000	$2000	19,822	35,735	784	1670		
	Over $175 k	$2000	$2000	4060	3371	440	526		
Policy 2: Uniformly decreasing rebates	Under $25 k	$2000	$1000	2899	6203	373	512	6999	155,655
	$25–$50 k	$2000	$1000	6065	18,191	614	846		
	$50–$75 k	$2000	$1000	10,313	18,667	528	639		
	$75–$100 k	$2000	$1000	6349	16,981	512	664		
	$100–$175 k	$2000	$1000	19,822	35,735	784	832		
	Over $175 k	$2000	$1000	4060	3371	440	255		
Policy 3: vehicle price cap at $60,000	Under $25 k	$2500	$1500	2899	6203	410	719	8651	157,308
	$25–$50 k	$2500	$1500	6065	18,191	649	1269		
	$50–$75 k	$2500	$1500	10,313	18,667	515	944		
	$75–$100 k	$2500	$1500	6349	16,981	507	995		
	$100–$175 k	$2500	$1500	19,822	35,735	847	1227		
	Over $175 k	$2500	$1500	4060	3371	194	377		
Policy 4: aggressive rebate increase with income cap	Under $25 k	$5000	$3000	2899	6203	1016	1515	13,471	162,128
	$25–$50 k	$5000	$3000	6065	18,191	1629	2610		
	$50–$75 k	$5000	$3000	10,313	18,667	1370	1954		
	$75–$100 k	$5000	$3000	6349	16,981	1342	2036		
	$100–$175 k	$0	$0	19,822	35,735	–	–		
	Over $175 k	$0	$0	4060	3371	–	–		
Policy 5: progressive rebate increase by income	Under $25 k	$7500	$4500	2899	6203	1635	2392	9434	158,090
	$25–$50 k	$5000	$3000	6065	18,191	1629	2610		
	$50–$75 k	$2000	$1000	10,313	18,667	528	639		
	$75–$100 k	$0	$0	6349	16,981	–	–		
	$100–$175 k	$0	$0	19,822	35,735	–	–		
	Over $175 k	$0	$0	4060	3371	–	–		

Table 8 (*continued*)

Policy	Income	BEV Rebate	PHEV Rebate	Baseline BEVs Sold	Baseline PHEVs Sold	Addt'l BEVs Sold	Addt'l PHEVs Sold	Additional PEVs Sold	Total PEVs Sold
Policy 6: Aggressive increase with price cap	Under $25 k	$5000	$3000	2899	6203	888	1515	12,452	161,108
	$25–$50 k	$5000	$3000	6065	18,191	1377	2591		
	$50–$75 k	$5000	$3000	10,313	18,667	1075	1915		
	$75–$100 k	$5000	$3000	6349	16,981	1069	2023		
	$100–$175 k	$0	$0	19,822	35,735	–	–		
	Over $175 k	$0	$0	4060	3371	–	–		
Policy 7: Progressive rebate with price cap	Under $25 k	$7500	$4500	2899	6203	1442	2392	8837	157,493
	$25–$50 k	$5000	$3000	6065	18,191	1377	2591		
	$50–$75 k	$2000	$1000	10,313	18,667	408	626		
	$75–$100 k	$0	$0	6349	16,981	–	–		
	$100–$175 k	$0	$0	19,822	35,735	–	–		
	Over $175 k	$0	$0	4060	3371	–	–		

Table 9
PEV rebate costs by type of policy.

Policy	Income	BEV Rebate	PHEV Rebate	BEV Budget	PHEV Budget	Total PEVs sold	Total cost ($ Millions)
Status Quo Policy	Under $25 k	$2500	$1500	$8,431,349	$10,383,030	158,335	$291
	$25–$50 k	$2500	$1500	$17,101,072	$29,202,579		
	$50–$75 k	$2500	$1500	$27,442,629	$29,444,460		
	$75–$100 k	$2500	$1500	$17,484,884	$26,973,264		
	$100–$175 k	$2500	$1500	$52,018,618	$55,478,170		
	Over $175 k	$2500	$1500	$11,541,233	$5,639,740		
Policy 1: Equaling rebates	Under $25 k	$2000	$2000	$6,545,083	$14,016,504	159,258	$319
	$25–$50 k	$2000	$2000	$13,358,461	$39,813000		
	$50–$75 k	$2000	$2000	$21,681,786	$39,913,772		
	$75–$100 k	$2000	$2000	$13,721,774	$36,646,760		
	$100–$175 k	$2000	$2000	$41,213,544	$74,811,156		
	Over $175 k	$2000	$2000	$9,000,554	$7,793,533		
Policy 2: Uniformly decreasing rebates	Under $25 k	$2000	$1000	$6,545,083	$6,714,527	155,655	$208
	$25–$50 k	$2000	$1000	$13,358,461	$19,036,334		
	$50–$75 k	$2000	$1000	$21,681,786	$19,305,549		
	$75–$100 k	$2000	$1000	$13,721,774	$17,644,670		
	$100–$175 k	$2000	$1000	$41,213,544	$36,566,955		
	Over $175 k	$2000	$1000	$9,000,554	$3,626,610		
Polciy 3: Vehicle price cap at $60,000	Under $25 k	$2500	$1500	$5,525,708	$8,734,800	157,308	$191
	$25–$50 k	$2500	$1500	$12,516,008	$26,627,751		
	$50–$75 k	$2500	$1500	$12,416,557	$20,625,015		
	$75–$100 k	$2500	$1500	$11,125,314	$23,355,006		
	$100–$175 k	$2500	$1500	$26,472,618	$40,322,793		
	Over $175 k	$2500	$1500	$2,510,984	$748,341		
Policy 4: Aggressive rebate increase with income cap	Under $25 k	$5000	$3000	$19,576,601	$23,152,788	162,128	$359
	$25–$50 k	$5000	$3000	$38,472,680	$62,401,798		
	$50–$75 k	$5000	$3000	$58,415,640	$61,862,019		
	$75–$100 k	$5000	$3000	$38,452,482	$57,049,903		
	$100–$175 k	$0	$0	$0	$0		
	Over $175 k	$0	$0	$0	$0		
Policy 5: Progressive rebate increase by income	Under $25 k	$7500	$4500	$34,009,626	$38,679,027	158,090	$215
	$25–$50 k	$5000	$3000	$38,472,680	$62,401,798		
	$50–$75 k	$2000	$1000	$21,681,786	$19,305,549		
	$75–$100 k	$0	$0	$0	$0		
	$100–$175 k	$0	$0	$0	$0		
	Over $175 k	$0	$0	$0	$0		
Polciy 6: Aggressive increase with price cap	Under $25 k	$5000	$3000	$13,441,267	$19,856,328	161,108	$266
	$25–$50 k	$5000	$3000	$28,674,486	$57,222,993		
	$50–$75 k	$5000	$3000	$27,636,150	$44,163,728		
	$75–$100 k	$5000	$3000	$25,057,919	$49,793,339		
	$100–$175 k	$0	$0	$0	$0		
	Over $175 k	$0	$0	$0	$0		
Policy 7: Progressive rebate with price cap	Under $25 k	$7500	$4500	$24,318,527	$33,734,336	157,493	$167
	$25–$50 k	$5000	$3000	$28,674,486	$57,222,993		
	$50–$75 k	$2000	$1000	$9,720,202	$13,432,334		

Table 9 (*continued*)

Policy	Income	BEV Rebate	PHEV Rebate	BEV Budget	PHEV Budget	Total PEVs sold	Total cost ($ Millions)
	$75–$100 k	$0	$0	$0	$0		
	$100–$175 k	$0	$0	$0	$0		
	Over $175 k	$0	$0	$0	$0		

Table 10
Comparison of policy performance metrics.

Policy	Additional PEVs Sold	Additional PEVs Sold*	Total Cost-Effectiveness	Addt'l Dollar Needed to Induce One Addt'l PEV*	Total Cost ($ Millions)	Total Cost* ($ Millions)	Allocative Equity
Status Quo Policy	9699	N/A	$30,017	N/A	$291	N/A	42%
Policy 1: Equaling rebates	10,602	903(+9%)	$30,044	+$27(+0.09%)	$319	+$27 (+9.4%)	42%
Policy 2: Uniformly decreasing rebates	6999	−2700(−28%)	$29,778	−$239 (−0.7%)	$208	−$83 (−28%)	42%
Policy 3: Vehicle price cap at $60,000	8,651	−1048(−10%)	$22,075	−$7942 (−26%)	$191	−$100 (−34%)	45%
Policy 4: Aggressive rebate increase with income cap	13,471	3772(+39%)	$26,677	−$3340 (−11%)	$359	+$68 (+23%)	73%
Polciy 5: Progressive rebate increase by income	9434	−265(−3%)	$22,743	−$7274 (−24%)	$215	−$77 (−26%)	100%
Policy 6: Aggressive increase with price cap	12,452	2753(+28%)	$21,349	−$8668 (−29%)	$266	−$25 (−8.7%)	72%
Policy 7: Progressive rebate with price cap	8837	−862(−9%)	$18,910	−$11,107 (−37%)	$167	−$124 (−43%)	100%

"Allocative Equity" is defined as the percentage of rebate dollars allocated to households with incomes under $75,000.
* Compared to Status Quo Policy.

receive can be determined through a few different methods. California provides fixed rebates, and the amount is lower for PHEVs than BEVs. Some other states, such as Massachusetts and Pennsylvania, provide fixed amount of rebates for vehicles with battery capacity above a certain threshold. Colorado, Maryland, and South Carolina determine the amount of incentive by battery capacity, and while they set a maximum amount for rebate, they do not fix the amount for which each vehicle model is eligible. In states like Illinois, Georgia, Louisiana, and West Virginia, PEV buyers multiply the MSRP by a percentage to determine the incentive amount they are eligible for; if the amount is above the maximum set by the state, they receive the maximum incentive available. New Jersey and Washington State provide sales tax exemptions for BEVs, but not PHEVs.

The California Clean Vehicle Rebate Projects currently provide rebates of $2500 for BEVs and $1500 for PHEVs. As of August 2014 this program had offered more than 50,000 rebates totaling over $100 million since its inception in 2010. Plug-in electric vehicles are also eligible to use high occupancy vehicle lanes in California until January 1, 2019.

Results and discussion

We use these simulations to evaluate a variety of alternative rebate policy designs, the results of which are presented in Tables 8–10. These results characterize the performance of alternative policy designs over approximately the next 3 years (i.e., 2014–2016) in California. They assume that consumers face the same choice set of PEVs and prices that are currently available in the California market and that annual new vehicle sales will be flat over the next three years.

5.1. Simulating the California status quo rebate policy

We first simulate the status quo rebate policy in California, which offers all income classes the same rebates of $2500 for the purchase of a BEV and $1500 for the purchase of a PHEV. Table 8 describes the baseline number of BEVs and PHEVs purchased by each income class (i.e., the number of BEVs and PHEVs that would have been purchased even if there was no rebate) as well as the additional vehicles induced by the policy design.

Micro-dynamics across income groups and vehicle technologies. Next we reflect on two observed patterns predicted earlier by our model that can be observed in the simulation results for the status quo rebate policy as shown in Table 8. First, these simulated estimates reflect the consumers' relative ex ante preferences for PHEVs over BEVs in nearly every income

Table 11
Optimal policy for the status quo budget.

		BEV	Rebate	PHEV	Rebate	Additional PEVs Sold	Total Cost Effectiveness	Total Cost
Optimal Policy	Under $25 k	$	12,500	$	7775			
	$25–$50 k	$	7400	$	2500			
	$50–$75 k	$	–	$	–			
						12,995	$ 22,394	$291,019,864
	$75–$100 k	$	2500	$	–			
	$100–$175 k	$	–	$	–			
	Over $175 k	$	–	$	–			

class, with consumers in several income classes purchasing 2 to 3 times as many PHEVs as BEVs. Second, in general, the lower income classes have lower ex ante values for both BEVs and PHEVs, purchasing fewer vehicles than do the middle and upper-middle income classes.[22]

We find that lower income classes are typically more responsive to the rebate dollars due to their higher marginal utility of income. Interestingly, consumers in the highest income class (above $175,000) appear to behave somewhat differently (see Table 8). Their ex ante value for PEVs is lower than that of the middle income classes, perhaps reflecting their preference for high performance luxury vehicles, which are less likely to be found among existing PEVs. In addition, unlike any other income class, they prefer BEVs (4060) to PHEVs (3371), revealing the importance of the Tesla Model S for this income class.

A cost-effectiveness measure. For the status quo policy, the total of additional vehicles purchased across all income classes is estimated to be 9699 over the next three years. In Table 9, we calculate the revenue costs by income group and by vehicle technology. Summing the rebates over vehicle type and income class gives us the estimated total status quo program costs of $291 million over the next 3 years. Dividing the additional vehicles purchased by the total cost gives us a policy cost-effectiveness measure which we calculate to be $30,017 per additional vehicle as shown in Table 10. For the status quo policy, every additional PEV purchased (over the baseline of what would have been purchased in the absence of rebates) requires California to spend $30,017 per vehicle. Our simulation suggests that 42% of the value of the rebates allocated goes to consumers making less than $75,000 under the status quo policy.

The cost effectiveness of the simulated policies is driven by the ratio of marginal to infra-marginal PEV purchases, as predicted in Section 3. Ultimately, the simulations suggest it is optimal to allocate higher rebates to products for which consumers have lower ex ante values (BEVs) and to consumers who have lower ex ante values (lower income consumers) because they have fewer infra-marginal purchases. The simulations also suggest it is optimal to allocate higher rebates to consumer sectors that are more responsive to the rebates (in this case, consumers with higher marginal utilities of income are more responsive) because they have more marginal purchases. In Table 11 we solve for the optimal rebate schedule that maximizes PEV sales, holding the budget equal to the status quo policy. This policy equalizes the ratio of marginal to non-marginal PEV purchases by allocating higher rebates to consumer-product segments with lower but steeper demand curves.

Comparisons with other rebate policies. Our model predicts that 148,636 PEVs would have been sold in the absence of the status quo policy. Note, though, that these consumers would still be eligible for the larger federal tax incentive (up to $7500) as well as local government rebates and reduced-cost parking and charging policies. We find that the current rebate, which has a weighted value across BEVs and PHEVs of about $1838, induces the purchase of 9699 PEVs, a 7% increase in PEV sales, or a 0.2% increase in total market share. As a point of comparison, Sierzchula et al. (2014) use ordinary least squares regression analysis of financial incentives in 30 countries to suggest that an increase in rebate level of $1000 is correlated with an increase in the observed market share of.06% for PEVs.

We are able to compare this estimate to two other types of vehicle rebate studies, those for hybrid electric vehicles (HEVs) and those for scrappage, or “Cash for Clunkers,” programs. Analyzing the Energy Policy Act of 2005, Jenn et al. (2013) find that for most vehicles, rebates levels in the $1000–$3000 range are correlated with a 7%–12% increase in sales. Gallagher and Muehlegger (2011) find that a tax incentive of $1000 is associated with a 3%–5% increase in sales for HEVs, while a comparable sales tax waiver is associated with a 45% increase in HEV sales. Analyzing the Canadian Hybrid Electric Vehicle rebate programs in different provinces, a Chandra et al. (2010) ordinary least square regression analysis finds that a rebate increase of $1000 is correlated with an increase in hybrid sales of 26%.

The federal and several state Cash for Clunkers rebate programs have been evaluated. Analyzing the Consumer Assistance to Recycle and Save Act (2009), Huang (2010) uses a regression discontinuity approach to infer that an $1000 rebate causes a 7% increase in sales of more fuel efficient vehicles. Gayer and Parker (2013) find the same program causes a 6–15% monthly increase in market share at various months during the program. Other evaluations include Li et al. (2013), Mian and Sufi.

We find that our estimate falls within the range produced by existing studies but is on the lower end of the distribution. That a rebate of a similar magnitude would be slightly less effective for PEVs than for HEVs or other fuel efficient vehicles

[22] The relative population shares of the income groups are 13% (Under $25k), 21% ($25–$50k), 18% ($50–$75k), 15% ($75–$100k), 24% ($100–$175k), and 9% (Over $175k).

should not be surprising for several reasons. First, PEVs require consumers behaviorally change their refueling practices, including purchasing an at-home charging station in most cases. Second, this study was conducted during a period of high unemployment and lower vehicle purchases than the timeframes utilized by some of the HEV studies that produced higher market share estimates (Gallagher and Muehlegger, 2011).

5.2. Changing rebate levels across vehicle technologies

Alternative rebate policies 1 and 2 explore the effects of equalizing the rebates and uniformly lowering the rebates across the vehicle technologies, respectively.

Equalizing rebates across vehicle technologies. Some observers have argued that PHEVs appear to generate similar magnitudes of electric miles traveled and should therefore be given rebate levels comparable to BEVs. Policy 1 illustrates what would happen in this market if policymakers reduce the BEV rebate by $500 (from $2500) and increase the PHEV rebate by $500 (from $1500), making the effective rebate for both vehicle technologies $2000.

To examine the effects of Policy 1, consider the response of consumers in the $25,000–$50,000 income class in Table 8. Compared to the status quo policy, these consumers will purchase slightly fewer additional BEVs (614 versus 775, a decrease of 161 vehicles or 21%) and modestly more PHEVs (1716 versus 1278, an increase of 438 or 34%). The large increase in PHEV purchases reflects larger consumer ex ante values for the PHEVs. Therefore, more consumers were relatively more likely to buy PHEVs even before their rebate was increased.

As a result of reducing the rebate on the BEVs by $500, its cost-effective measure (BEV budget divided by additional BEVs sold) improves (falling from $32,691 to $32,445 per vehicle). However, the reverse is true for the $500 increase in rebate levels for PHEVs, causing PHEV cost-effectiveness (PHEV budget divided by additional PHEVs sold) to fall (rising from $28,059 to $28,981 per vehicle) compared to the status quo policy. The net effect is to slightly worsen total cost effectiveness of the policy to $30,044 per induced PEV purchase versus $30,017 under the status quo policy. Thus, even if the magnitude of the positive externality associated with driving a PHEV were equal to that of driving a BEV, our analysis suggests that equalizing the rebate would not be a cost-effective use of public funds. Consideration needs to be given not just to the change in the total number of PHEV vehicles sold under Policy 1 but also to the revenue opportunity costs.

This effect also is seen at the programmatic level. In comparing the status quo policy with Policy 1 of equal rebate levels, many more additional vehicles are sold under Policy 1, increasing from 9699 to 10,602, an increase of 9% in the number of additional PEVs purchased, which is driven by a 30% in the number of additional PHEVs purchased. The total cost of the program rises from $291 million to nearly $319 million. This is largely because Policy 1 increases the rebate by $500 to the 99,148 consumers who would have purchased a PHEV in the absence of any rebate, and even though it induces an additional 7349 PHEVs to be purchased. This is offset slightly by a $500 rebate reduction to the 49,508 BEVs that would have been purchased without the policy and a reduction in the number of additional BEVs sold by only 848.

In summary, increasing relative rebates on vehicle technologies with relatively higher consumer ex ante values increases the total additional number of vehicles purchased ceteris paribus. However, increasing relative rebates on vehicle technologies with relatively higher consumer ex ante values *worsens the cost-effectiveness* of the overall program since it increases the magnitude of the rebate payouts to those who would have purchased the higher valued vehicle technology anyway.

Uniformly reducing the rebate levels across technologies. Policymakers might consider uniformly reducing rebate levels because budgetary pressure or a belief that government interventions are no longer justified. In Tables 8 and 9, Policy 2 reduces both the BEV and PHEV rebate levels by $500, from $2500 and $1500, respectively. In comparison with the status quo policy, we observe consumers in all income classes purchasing fewer additional PHEV and BEV vehicles. The total reduction in additional vehicles can be observed by comparing the 6999 additional vehicles purchased under Policy 2 with the 9699 additional vehicles purchased under the status quo policy, a difference of roughly 2700 additional vehicles or a 28% reduction. Total policy costs fall by over $80 million since both the eligible consumers in the baseline and additional consumers all receive lower rebates by $500. However, because of the commensurate fall in the number of additional vehicles under Policy 2, the cost-effectiveness performance of Policy 2, relative to the status quo, improves only a small amount, falling from $30,017 to $29,778. While uniformly lowering the eligible rebates does lower total program costs, it improves cost-effectiveness only minimally.

Allocative equity with reduced rebates. Some policymakers have suggested reducing rebate levels because they view the status quo policy as favoring wealthy consumers. We are able to evaluate the allocative impacts of moving from the status quo policy to a reduced rebate level policy, such as alternative Policy 2, which achieves a uniform reduction of $500 in all rebates. What we observed is that allocative equity does not change greatly when levels are reduced. We use the percent of rebates allocated to consumers with incomes of less than $75,000 as a measure of allocative equity. The status quo policy allocates 42% of rebates to consumers with incomes less than $75,000 while Policies 1 and 2 also allocate approximately 42% to similar consumers.

5.3. The effect of a vehicle price cap on rebate eligibility

Recently policymakers at the California Air Resources Board have proposed a price cap as means to increase the effectiveness and equity of California's rebate policy. Such a policy design would allow only vehicles below a certain price level to qualify for a rebate. For Policy 3, we consider a vehicle price cap of $60,000, the results of which we present Tables 8–10. For the California market, Policy 3 would historically exclude only the Tesla Model S (a BEV) from a rebate but would prospectively also exclude the Porsche Panamera and the Cadillac ELR (both PHEVs) from a rebate. Our vehicle choice model captures the consumer response for all of these vehicles.

The results of making only vehicles under a price cap of $60,000 eligible for the current rebates are shown in Tables 8–10 by comparing Policy 3 with the status quo. Focusing on where the relative impacts are likely to be greatest, consider consumers with incomes over $175,000 for Policy 3. While these wealthy consumers purchase slightly fewer additional PHEVs (377 vs. 389), they purchase many fewer BEVs (194 vs. 557) when shifting from the status quo to a price cap of $60,000. If the policy goal was to give Tesla owners fewer rebates, then this approach appears to succeed. Smaller reductions in relative purchases of PHEVs and BEVs occur for consumers in the other income classes, reflecting the fact that fewer of them are affected by a price cap of $60,000.

In aggregate, the shift from the status quo to a price cap results in a reduction in the total number of additional vehicles being sold (8651 vs. 9699, a 10% reduction). This policy design also significantly improves the cost-effectiveness of each additional vehicle sold, causing the cost to fall substantially from $30,017 to $22,075, a 26% reduction. What is perhaps most surprising is how much the total program costs fall, from $291 million to $191 million, a reduction of around $100 million, or 34%. The policy decision here may hinge on beliefs about how much technology from these high end vehicles gets filtered down later to other market segments, for example, with Toyota's adoption of a substantial amount of Tesla technology into a BEV version of its popular RAV 4.

5.4. Income-tested rebate policies

Another proposed approach to redesigning the existing rebate program is to give consumers in lower income classes relatively higher rebates. Policymakers may choose to do this because either they know that targeting rebates towards consumers with lower ex ante values will improve cost-effectiveness or because they are concerned about improving this program's allocative equity. There are several designs this policy could take.

Policy 4 assesses an increase in rebate levels but also a cap on income eligibility, meaning consumers above a specified income ($100,000 for this policy) do not qualify for the rebate. All consumers making less than $100,000 would receive a rebate of $5000 for BEVs and $3000 for PHEVs. Compared to the status quo policy, this policy design results in significantly more additional PEVs being sold; increasing from 9699 to 13,471 for a 3772, or 39% increase. This policy design also represents an increase in cost-effectiveness, dropping from $30,017 to $26,677 for a $3340 reduction, or an 11% improvement. However, despite reduction in dollars spent per additional vehicle, the 39% increase in the additional number of vehicles sold caused the total cost of this policy design to increase from $291 million for the status quo to $359 million, for an increase of over $68 million, or 23%. Allocative equity increases from 42% for the status quo policy to 73% for this policy. Thus, this policy design improves the number of additional PEVs sold, policy cost-effectiveness, and allocative equity but it does substantially increase the total cost of the program.

We next consider a progressive rebate schedule, which is designed to bring down total program cost. Policy 5 offers progressive rebate levels with an income cap. For BEVs, this policy would offer consumers making 1) less than $25,000, a rebate of $7500, 2) $25,000–$50,000, a rebate of $5,000, 3) $50,000–$75,000, a rebate of $2000, and 4) over $75,000, no rebate. Consumers purchasing a PHEV in these same income categories would receive $4500, $3000, and $1000, respectively. This policy results in approximately the same number of additional PEVs being sold as does the status quo policy: 9434 vehicles compared to 9699 vehicles for the status quo. This policy is also among the most cost-effective, comparable to the price cap policy (3) at $22,743 per additional PEV compared to $22,075 for the price cap policy. Its total policy costs are also among the lowest of any policy considered so far. This policy has total cost of $215 million compared to $291 million for the status quo policy, a reduction of $77 million or 26%. This policy scores 100% on our allocative equity measure since all of the rebates go to consumers making less than $75,000. *Policy 5 is therefore superior to the status quo policy along all policy performance dimensions.*

5.5. Income-tested policies with price caps

Lastly, we may try to improve these income-tested policies by adding price caps. Intuitively, we expect the addition of a vehicle price cap to reduce the number of additional vehicles sold but also to improve the cost-effectiveness measure, reduce total costs, and possibly to improve allocative equity.

Policy 6 evaluates the addition of a vehicle price cap of $60,000 to Policy 4 (Policy 4 generated the largest number of additional PEVs purchased, improved cost-effectiveness, and allocative equity but did so at the largest program costs.). Adding a vehicle price cap as in Policy 6 causes approximately 1000 fewer vehicles to be purchased compared to Policy 4 but this still represents a 2753 or a 28% increase in additional vehicles purchased over the status quo policy. Cost-effectiveness improves significantly falling from $26,667 to $21,349 per additional vehicle purchased when comparing policies 4 and 6. Allocative equity is about the same across the policies 4 and 6. However, total program cost falls dramatically from $360 million to $266 million, a $54 million or 15% reduction comparing policies 4 and 6. It should be noted that Policy 6 costs of $266 million are less than the $291 million of the status quo program. Policy 6 represents an improvement over the status quo policy along all performance dimensions.

Policy 7 adds a vehicle price cap to Policy 5, which has a progressive rebate schedule capping income eligibility at $75,000. Recall that Policy 5 was already superior to the status quo policy along all dimensions. However, adding the vehicle price cap reduces the additional number of vehicles sold to 8837 from 9699 under the status quo policy, a reduction of 862 vehicles or 9%. While a net reduction in the number additional vehicles sold may be viewed as an unacceptable consequence of this policy by some, it does produce the greatest improvement in policy cost-effectiveness, reducing public dollars spent per additional vehicle from $30,017 to $18,910, a reduction of $11,007 or 37% per vehicle. It also reduces the total program costs from $291 million to $167 million, a savings of $124 million, or 43%.

Conclusion

Our objective has been to illustrate how commonly used "second-best" policies can leverage several types of heterogeneity across consumers or products in order improve policy performance. These include differences in consumers' ex ante value (i.e., willingness to pay) for specific technologies, their marginal utility of income, and the price levels of the technologies. These difference can be used to improve a broader set of policies that rely on price subsidies, rebates, tax credits, sales tax exemptions, and subsidized financing to target consumers' adoption of technologies such as alternative fuels and vehicles, energy and water efficient technologies, and renewable energy technologies, among others.

As we show, the economic information needed to identify how to incorporate consumer heterogeneity can be obtained from relatively simple empirical consumer choice studies. Even in the case of mis-measurement, e.g., if the estimated price elasticity of demand is inaccurately estimated, the basic tenants of our theoretical model and proposed policy modifications still hold. The results of our policy simulations would be the same in direction though likely of increased or decreased magnitude.

Our basic approach enables economists to identify feasible superior policy designs. Our specific analysis suggests that policymakers can re-design PEV rebate programs such as California's to induce the sale of more PEVs, achieving greater allocative equity at a lower total cost to the state taxpayers. First, we focus on two policy designs that have the ability to 1) increase total or hold constant the additional PEVs purchased, 2) decrease total government costs, and 3) increase allocative equity. Our analysis of Policy 5 shows that without a significant reduction in the number of additional PEVs purchased, we could dramatically increase allocative equity while saving $77 million compared to the current policy. Similarly, Policy 6 offers the greatest number of additional PEVs sold (28% greater than the status quo) for a policy that costs less (by 9%) than the status quo policy.

Appendix A

See Fig. A1.

Make	Body	Model	Type	MSRP	Range	Refuel (mpge)	Refuel $/gal
Smart	convertible		BEV	$ 28,000	68	107	0.77
Smart	hatchback		BEV	$ 25,000	68	107	0.77
Chevrolet	compact sedan	Volt	PHEV	$ 34,185	38	98	0.84
Ford	compact sedan	Focus Electric	BEV	$ 35,170	76	99	0.83
Toyota	compact SUV	RAV4 EV	BEV	$ 49,800	103	74	1.11
Chevrolet	hatchback	Spark	BEV	$ 26,685	82	109	0.76
Chevrolet	hatchback	Spark	BEV	$ 27,010	82	109	0.76
Fiat	hatchback	500 Elettrica	BEV	$ 31,800	90	108	0.76
Honda	hatchback	Fit EV	BEV	$ 36,625	82	105	0.78
Nissan	hatchback	Leaf	BEV	$ 29,650	73	102	0.81
Nissan	hatchback	Leaf	BEV	$ 32,670	73	102	0.81
Nissan	hatchback	Leaf	BEV	$ 35,690	73	102	0.81
Toyota	hatchback	Prius Plug In	PHEV	$ 30,800	11	95	0.87
Toyota	hatchback	Prius Plug In	PHEV	$ 35,715	11	95	0.87
Chevrolet	coupe	Cadillac ELR	PHEV	$ 75,000	37	98	0.84
Porsche	full-size sedan	Panamera S E-Hybrid	PHEV	$ 99,000	20	98	0.84
Tesla	midsize sedan	Model S	BEV	$ 71,070	265	94	0.88
Tesla	midsize sedan	Model S	BEV	$ 81,070	265	94	0.88
Tesla	midsize sedan	Model S	BEV	$ 94,570	265	94	0.88
Ford	midsize sedan	Fusion Energi	PHEV	$ 35,525	21	92	0.90
Ford	midsize sedan	Fusion Energi	PHEV	$ 37,325	21	92	0.90
Honda	midsize sedan	Accord Plug In	PHEV	$ 39,780	10	105	0.78
Ford	wagon	C-Max Energi	PHEV	$ 32,920	21	100	0.82

Fig. A1. PEVs on the market as of fall 2013.

Appendix B. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2017.01.002.

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