# Minimizing Fleet Emissions through Optimal EV Subsidy Design and Vehicle Replacement

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**Abstract**

The bulk of federal- and state-level subsidy programs for electric vehicles (EV) offer these funds at a flat rate. If the goal of these initiatives is to minimize vehicle emissions, the flat subsidy design ignores several issues a more efficient program should feature. The first is that funds should target marginal consumers whose likelihood to purchase EVs increase most with the vehicle subsidy. The second that the subsidies are directed toward consumers most likely to impact emissions by replacing less energy efficient vehicles. The goal of the work is to propose a subsidy design which maximizes the expected reduction of emissions per dollar spent by targeting marginal consumers with the highest impact on vehicle emissions. In this version we exploit spatial discontinuities in California's local subsidy programs and zip code-level vehicle purchase and registration data to characterize consumers along key demographics, such as income and vehicle ownership, in describing their responsiveness to EV incentives. Using vehicle stock and replacement behavior, we can then sort these consumers by how much their vehicle replacement would reduce emissions.

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# 1 Introduction

In the wake of mounting attention toward investment in energy efficiency and renewable resources, the US allocated approximately $400 million of the 2009 American Recovery and Reinvestment Act (ARRA) in part toward investment and research into electric vehicles (EVs). State and municipal governments, notably in California, concurrently rolled out other incentive programs to encourage the adoption of electric cars, including hefty rebates, tax credits, and electricity discounts. These programs, however, are intermediate steps to the larger goal of reducing carbon emissions from the vehicle fleet. Recent research has redirected its attention toward the question of how effective these program are at improving fleet efficiency.

For a policy maker designing a subsidy program to minimize fleet emissions, several factors disconnect this objective from maximizing EVs on the road. The first requires accounting for power grid emissions when charging an EV as compared to the comparable emissions from driving a gas vehicle. Holland et al. (2016) address this issue and find even as of 2012 the impact of driving electric vehicles has a net positive impact on carbon emissions everywhere in the US. A second issue is determining what vehicles consumers replace when purchasing a new vehicle. The net emission impact of replacing a Tesla with a newer Tesla is substantially different than replacing a mid 90s Toyota Camry. This dimension is similar to yet distinct the substitution question, addressed in papers like Xing, Leard and Li (2019), that is what vehicles would consumers purchase in the absence of a subsidy regime.

In this paper we address this second set of factors with the ultimate goal of proposing an optimal subsidy design to maximize the expected reduction of emissions per dollar spent. Theoretically, we consider a Pigouvian subsidy design through the lens of a policy maker has instruments that discriminate based on income (or vehicle type). How large this subsidy should be is then dependent on the marginal emissions contribution of the consumer per unit of the subsidy offered. The policy maker should target subsidies toward marginal consumers, that is those whose vehicle emissions, from a social perspective, are most sensitive to the subsidy.

The impact a consumer has on fleet-wide emissions is not only dependent on the purchase behavior of the consumer. Identifying marginal consumers requires consideration of both a targeted consumer's vehicle replacement and induced substitution from a subsidy. In the simplest case when we limit a consumer to a single car, she can impact emissions in two ways. The first is to introduce a more efficient vehicle into the fleet. The second is to remove a low mileage vehicle from the fleet by scrapping it.[1]

Ultimately, identifying these marginal consumers is an empirical question. We characterize them in the context of the California electricity market over the period 2014 to 2016, during most of which the state offered flat subsidies based on vehicle efficiency. As we detail in Section 2,

[1]This story we focus on ignores other potential issues that could likely only be remedied with a finer policy tool, like lifetime vehicle usage.

the period is particularly interesting for study as municipalities in California implented their own financing programs and the state began to introduce a progressive subsidy schedule. To some extent we treat the cut offs and regional plans as a source of exogenous variation in subsidy levels to help identify price elasticities.

We pair the setting with a unique combination of granular, vehicle-level purchase and ownership data to start addressing these questions. With the high spatiotemporal variation in subsidy levels in California from localized vehicle incentive programs, the discontinuities permit a cleaner analysis of the impact of these policies on the consumer choices described previously. In this version of the paper, we simply use the discontinuities to link replacement behavior to income and subsidy levels. We separately identify the responsiveness of different income groups to these subsidies through a stated preference survey of California drivers. To our knowledge we are the first paper to approach the question of designing these EV incentives from the perspective of fleet-wide emissions.

This paper contributes to the growing literature on the efficacy of subsidy programs to induce demand for green products, in particular electric vehicles. Muehlegger and Rapson (2018) studies funds targeted toward lower income households in California and estimate an average effect from a flat \$1000 subsidy generates a 15% increase in sales, depending on the specific market. DeShazo, Sheldon and Carson (2017) focuses on the design of these subsidies along consumer income levels and identify low-income consumers as the marginal class based on a custom survey. Xing, Leard and Li (2019) find similar results using a wider dataset in the United States. Identifying that the subsidy elasticity of EV demand varies across income groups relates to findings from Borenstein and Davis (2016) and West (2004), which both show vehicle subsidies are large taken up by the highest income groups.

As we discuss, adoption rates cannot be taken in isolation when considering minimizing fleet emissions through an EV subsidy. Two recent papers address the issue of choice substitution. Chen, Hu and Knittel (2017) addresses this point through a study of the market for EVs in China. They find that most subsidies are taken up by consumers who would have purchased relatively efficient vehicles even in the absence of the subsidy. Xing, Leard and Li (2019) also addresses a similar set of questions in the context of the US market. They find 70% of federal program dollars were spent by consumers who would have purchased an EV without the subsidy. Consumers that do substitute tend to from vehicles with a fuel economy higher than the fleet average.

A related literature studies adoption cases with consideration for dynamics. Springel (2017), Li (2017), Li et al. (2017), and Zhou and Li (2018) all study the important relationship of electric vehicle adoption and their charging station infrastructure. The build out of the infrastructure over time increases the value of electric vehicles to consumers independent of tastes and subsidies. Springel (2017) explicitly models charging stations subsidies as an alternative and competing design for a policy maker to maximize EV adoption. While we do not focus on this element in this paper, we do control for the potential of charging stations to consumers.

The new element of this work is to consider additionally how subsidies impact the replacement behavior of consumers and its interaction with the vehicles they already own. This feature is related to recent work by Langer and Lemoine (2018), which looks at optimal subsidies in the context of durable goods that improve over time with an application to residential solar panels. The key features of this model are consumers whose tastes change over time and can manipulate purchase behavior based on announced subsidy schedules. Curiously, Chen, Hu and Knittel (2017) do not find evidence of "manipulative" intertemporal substitution in the Chinese vehicle market. Our contribution to the dynamics of designing EV subsidies is solely along the angle of replacement. Several papers — Chen, Esteban and Shum (2010), Mian and Sufi (2012), Adda and Cooper (2000), Schiraldi (2011) — document the impact of subsidy or scrappage bonuses on intertemporal replacement behavior in general vehicle markets.

The rest of the paper proceeds as follows. Section 2 describes the existing electric vehicle subsidy structure in California. Section 3 introduces the granular operating vehicle data we use in the empirical analysis. Section 4 details the empirical strategy for the reduced form exercises and presents the results. The conclusion discusses these results and the implications for the full paper designing an optimal subsidy structure.

## 2 Purchase Incentives for Electric Vehicles in California

In this section we detail the subsidy incentives available to EV purchasers in California. In particular we demonstrate the spatial and temporal variation in prices offered by local-level programs. Complementary information on the construction of the data itself is in Appendix A.2.

### 2.1 Subsidy Structure and Data

While the market has changed significantly in the past decade, electric vehicles still tend to have higher upfront prices than gas vehicles. Toward the beginning of our period of study in 2013, the most popular fully electric vehicle, the Nissan LEAF, had a $28,800 baseline price tag in 2013. In contrast the Honda Civic, the most popular vehicle, cost only $16,555. The most expensive electric vehicle, the Tesla Model S, which cost at least $69,900 at the time, while the most expensive gas vehicle among the top 80 CA car models in 2013 had an MSRP of $52,800.[2]

When purchasing electric vehicles consumers in California can enjoy benefits from up to a three-tiered subsidy system. The first are the nationwide "Plug-In Electric Drive Vehicle Credit" funds available from the federal government.[3] This program offers somewhere between $2,500 and $7,500 depending on the fuel economy of the vehicle. Many plug-in electric vehicles (PEVs) enjoy the full credit while plug-in hybrid electric vehicles (PHEVs) vary between the two extremes. These funds,

[2] Comparisons of the full list of EVs available at the beginning of our study period are in Table A.1.

[3] The program has a phase out when manufacturers sell enough vehicles, but they have only initiated for two manufacturers — Ford and Tesla — well past the period of study.

while they vary with the fuel economy of the vehicle purchased, are offered at a flat rate regardless of demographics.

The state of California offers the second tier of subsidies through the Clean Vehicle Rebate Project (CVRP). For most of the period covered in this research, 2014 through 2016, these subsidies were offered at a flat rate and dependent only on the fuel economy of the vehicle purchased. As of March 29, 2016, the program limited the availability of funds to high income earners and introduced an additional $1500 to households at or less than 300 percent of the federal policy line. These limits changed again in November 2016 with a reduction in the high income cap and a $2000 additional subsidy available to low-income households. Table 2.1 summarizes the potential subsidy from these first two programs prior to the eligibility changes.

Table 2.1: **Federal and CA State Incentives for EV Purchases, through March 29, 2016**

| | Clean Vehicle Rebate Project | Federal Tax Credits[a] |
|---|---|---|
| Project Period | 2010 - current | 2009 - current |
| Area Covered in CA | All | All |
| Funding Institute | California Air Resources Board | IRS |
| Funding Amount | $58.5 million dollar | Until manufacturer sells 200,000 |
| Rebate Amount | $1,500 to $2,500 | $2,500 to $7,500 |
| LEAF Rebate | $2,500 | $7,500 |
| Volt Rebate | $1,500 | $7,500 |
| Prius Rebate | $1,500 | $2,500 |
| Eligibility | Zero emission, plug-in hybrid | Zero emission, plug-in hybrid |
| | Battery, Hydrogen Fuel EV | Only battery EV |

[a] Plug-in Electric Drive Vehicle Credit (IRC 30D) by IRS

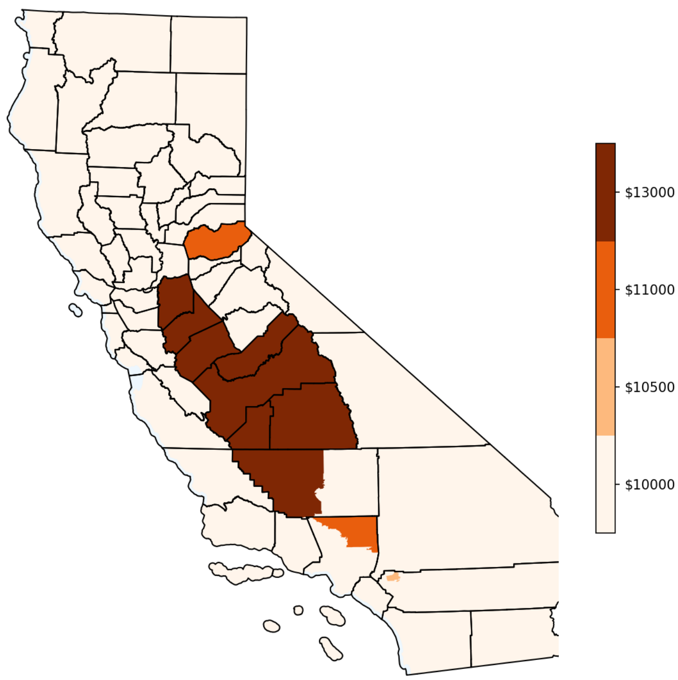
While the CVRP changes serve as a policy shock during the period of study, our analysis depends principally on spatial differences in eligible funding. This variation is offered by the expansive third tier of funding available in California at the air district and municipality level. The "Drive Clean" website produced by California Air Resource Board compiles all of these incentives and allows California residents to query what subsidy options are available to them based on their residence. The number and magnitude of these subsidies varies highly across the state. For example, the Los Angeles zip code 90210, yields three *potential* local — on federal or state — level EV subsidies. The consumer living in Southern California Edison's electricity service area could receive a $450 rebate for new or used EVs; Antelope Valley offers a $1,000 rebate for EVs purchased in qualifying zipcodes, and the South Coast Air Basin District runs a low-income replacement program detailed in Muehlegger and Rapson (2018). We provide details of how we constructed the local subsidy data in Appendix A.2.[4]

The local subsidies introduce substantial spatial and temporal variation in EV prices net of

[4] As our vehicle registration data is available at the zip code level, part of the construction task is identifying which zip codes are not "split" by multiple subsidy programs not available to all consumers in the district. For example, only part of 90210 is covered by Southern California Edison.

subsidies across California. It is difficult to demonstrate the full variation in prices, as it depends on time of purchase and household income. Figure 2.1 illustrates the available subsidies for a person with $60,000 in household income purchasing a PEV, as of December 2014. At this point, the San Joaquin Valley Air Pollution Control District offered the most generous subsidies. As mentioned, the landscape of these local subsidy programs changes significantly over time; Figure A.1 illustrates the increasing rate of new programs introduced toward the end of our period of study.

Figure 2.1: **Plug-in Electric Vehicle Subsidy Available, December 2014**




*Notes:* The subsidy map assumes a person with a $60,000 income is purchasing a plug-in electric vehicle. The coloration denotes maximum available subsidies, assuming full uptake, for a person residing in the area.
*Source:* Local subsidies by zip code are available on driveclean.ca.gov.

## 2.2 Other Incentives

Another set of significant financial incentives for consumers are Enhanced Fleet Modernization Programs, which are the key policy of interest in Muehlegger and Rapson (2018). These cash-for-clunker-like policy programs, while financially generous, are significantly more restrictive than the subsidies detailed at the beginning of this section. The funding is restricted to low income consumers — no more than 400% of the poverty line — and require legwork like attending special events. As a result, we choose not to include this particular set of incentives in our study; Muehlegger and

Rapson (2018) find the subsidies are only used in 2% of purchases in the eligible areas of California.[5]

Other incentive programs, like home charging station subsidies and time-of-use rate discounts from utility providers, are modeled as part of the cost of purchasing an EV. These details are covered in Appendix A.3. There are other incentives we do not explicitly consider in the paper, however. For example, limited numbers of PHEVs and fully electric vehicles can gain access to HOV lanes on California highways. While this program could easily be more valuable than any monetary benefit to those that ahve to endure Los Angeles traffic, this work focuses solely monetary incentives.[6]

### 2.3 Linking EV Subsidies to Emissions Reductions

We use a simple, stylized framework to describe how a policy maker attempting to minimize fleet emissions can anticipate the impact of an EV subsidy on this objective.

Let $\{0, \ldots, J\}$ be the set of available vehicles in the market, either used or new. For simplicity these vehicles are identified by their fuel efficiency $mpg_j$. For an electric vehicle consider this measure the standard *miles per gallon equivalent*. Let $j = 0$ denote the option of not purchasing any car.

Assume some consumer $i$ currently owns a car with characteristic $mpg_{j(i)}$, where $j(i)$ indicates the model owned by consumer $i$. For notational simplicity, let $mpg_{j(i)} \equiv oldmpg_i$. Every period the consumer has the option to purchase a vehicle and subsequently get rid of her old vehicle by selling it in the used car market or scrapping it. Let $mpg_i$ denote the $mpg$ of the new vehicle chosen, should the consumer choose to switch her car.

The final piece is to consider the *change* in this consumer's purchasing behavior from exposure to the EV subsidy. We can write down the expected *change* in the fuel efficiency of the vehicle the consumer purchases as

$$\begin{aligned}\Delta E[mpg_i|subsidy_i] = \sum_{j\in J} [&(mpg_j Pr_i(j|subsidy_i, j \neq 0) - oldmpg_i) * Pr_i(j \neq 0|subsidy_i) \\ &- (mpg_j Pr_i(j|j \neq 0) - oldmpg_i) * Pr_i(j \neq 0)] \qquad (1)\end{aligned}$$

The marginal consumers can be ranked by the magnitude of $\Delta E[mpg_i|subsidy]_i$. Equation 1 shows we can break down how these marginal consumers are determined into two components. The first is how the subsidy increases the consumer's probability of purchasing a more fuel efficient vehicle.

[5]In mid 2018 the state of California introduced a similar, yet mutually exclusive, lower-income program called the Clean Vehicle Assistance Program. Grant recipients are not only eligibile for a straight subsidy but also financing assistance.

[6]In fact according the Center for Sustainable Energy (2013) survey of PEV users, 59% claimed HOV access was an "important" consideration in their purchase decision.

Imagine $Pr_i(j \neq 0|subsidy_i) = Pr_i(j \neq 0) = 1$, the expected change in mpg is

$$\sum_j mpg_j \left[Pr_i(j|subsidy_i, j \neq 0) - Pr_i(j|j \neq 0)\right]$$

We call this difference the **substitution channel**. The second factor contributing to a consumer's responsiveness to the subsidy is the **replacement channel**. This factor manifests in the difference $Pr_i(j \neq 0|subsidy_i) - Pr_i(j \neq 0)$. As we eventually aim to show, these probabilities should be a function of current vehicle ownership (see for example Schiraldi (2011)). It is an open empirical question whether it is first or second-order concern developing the most cost effective subsidy scheme.

# 3 Data

## 3.1 Data Description

We use three principal sources for our information on purchased and operating vehicles in California. The marketing firm IHS provides us the most comprehensive set of registration data. This data set includes the universe of new car registrations in California for the years 2014 to 2016 at the zip code and monthly level. Because we study the emissions of the whole operating fleet, we also obtain records of all vehicles in operation by the zip code of their operation. This accounting is done at the end of every year for years 2014 to 2016. Finally, to understand the linkage between the secondary vehicle market and the change in operating vehicle records — versus, for example, vehicle owners moving — we make use of used car registrations for 2016 at the monthly level.

We complement this principal source with two secondary data sets. The first records are new EV registration records from the Clean Vehicle Rebate Project (CVRP), which provides subsidy records for every eligible electric vehicle purchaser that sought a rebate. The second is the California Vehicle Survey (CVS) conducted by the California Energy Commission (CEC) in late 2016.[7] The CEC is a survey of approximately 3600 households that asks, among other points like demographics and travel behavior, what vehicles the household owns, their purchase history, and their *intended* purchase behavior in the future. Because the IHS data do not allow us to track household-level decisions, in particular the vehicle replaced when a new or used car is purchased, the CVS provides a necessary complement to these sources. While the CVS witholds vehicle models, the public survey does report the make, fuel type, and mileage of the current vehicle owned. The next section provides more details on the survey conducted by the CVS, a survey we will use for one set of reduced form exercises. For aggregated demographic information, like income distribution and population, we use the yearly American Community Survey.

[7] For details on how the CEC carried out the component surveys of the CVS, see Fowler et al. (2018).

We collect standard vehicle characteristics from AutoTrader.com and Edmunds. These characteristics include the standard features as in Berry, Levinsohn and Pakes (1995) as well as driving range and fuel type. We assume that the fuel efficiency of a vehicle is given from its combined city and highway ratings. In a dynamic model of vehicle replacement an extra consideration, see for example Schiraldi (2011), is the value of a consumer holding on to the vehicle already owned. This value is in part decided by the expected resale value of that vehicle. As a proxy for the expected resale value we link model vintages to recommended resale prices from the Kelley Blue Book (KBB). We scraped these values from historical KBB publications for every quarter from 2014 to 2016.

Working with granular vehicle data over time requires controlling for other factors that have been shown to affect demand for electric vehicles. We collect the status of the charnging station network principally from the Alternative Fuels Data Center (AFDC), which in turn collects from major charging stations operators, equipment manufacturers, among others. For every zip code and time period we determine a count of "home" and "work" charging stations, the latter generated by a weighted average of charging stations located in the work zip codes of residents in the home district.[8] Other research has emphasized the role of political peer pressure or political preference as an influence on taste for green products.[9] We follow Sexton and Sexton (2014) and others in generating a market "greenness index" for each market. This index is generated from yearly Federal Election Commission (FEC) voter registration and donation reports. Further details about the construction of these data are in Appendices A.3 and A.4.

### 3.2 Summary Statistics

Since the first set of exercises in the following section look at the income group-based sensitivity to EV subsidies, we first report some vehicle-type purchase statistics. Figure 3.1 reports the share of new vehicle sales PEV and PHEV vehicles composed in Q1 2014 and Q4 2016. Across the board we see a reduction in the purchase of PHEVs in favor of PEVs, surely in part due to the changing choice set. Second, percentage growth in PEV purchases dominates as income class descends, but high-income earners still purchase the most PEV and PHEVs. The first set of exercises in the next section will begin to dissect whether this trend is from price or preference. Table A.3 in the Appendix reports similar patterns across income groups for the sale of used EVs.

Table 3.2 reports actual, average fuel efficiency of vehicles in operations in areas of particular income groups, fuel efficiency tends to increase with income. Along with Table 3.1 a reasonable inference for why — and why fuel efficiency has increased more in high income areas — are the EV sales patterns. Unsurprisingly this improvement in fleet efficiency is matched by increasing fuel efficiency in new cars.

[8]Unpublished work in the dissertation of author Matthew Shapiro documents the importance of distinguishing between home and work charging stations for demand estimation at this level of granularity.

[9]See, for example Kahn (2007), Costa and Kahn (2013), Delmas, Kahn and Locke (2014).

Table 3.1: **EV Sales Shares by Income Category, Q1 2014 and Q4 2016**

| Type | Income | Q1 2014 Sales Share | Q4 2016 Sales Share | Percent Change |
|---|---|---|---|---|
| PEV | Less than $49,999 | 0.0055 | 0.0083 | 0.51 |
| | $50,000 to $74,999 | 0.0103 | 0.0155 | 0.50 |
| | $75,000 to $99,999 | 0.0179 | 0.0256 | 0.43 |
| | $100,000 to $149,999 | 0.0374 | 0.0520 | 0.39 |
| | $150,000 or more | 0.0563 | 0.0759 | 0.35 |
| PHEV | Less than $49,999 | 0.0527 | 0.0468 | -0.11 |
| | $50,000 to $74,999 | 0.0746 | 0.0624 | -0.16 |
| | $75,000 to $99,999 | 0.0948 | 0.0780 | -0.18 |
| | $100,000 to $149,999 | 0.1147 | 0.0915 | -0.20 |
| | $150,000 or more | 0.1313 | 0.1062 | -0.19 |

*Notes:* Shares are calculated by dividing the sum of cars of a fuel category sold over all vehicles sold in zip codes with a median income in bracket specified.

Table 3.2: **Fuel Efficiency of Cars in Operation by Income Group**

| Income | 2014 | 2015 | 2016 | 2014 to 2016 Change |
|---|---|---|---|---|
| Less than $49,999 | 22.848 | 23.081 | 23.361 | 0.022 |
| $50,000 to $74,999 | 22.925 | 23.178 | 23.492 | 0.025 |
| $75,000 to $99,999 | 22.926 | 23.210 | 23.569 | 0.028 |
| $100,000 to $149,999 | 22.997 | 23.318 | 23.687 | 0.030 |
| $150,000 or more | 22.831 | 23.213 | 23.678 | 0.037 |

*Notes:* Average fuel efficiency reported is the average efficiency of all vehicles in operation registered to a zip code with a median income in the listed income category as of the end of that year.

# 4 Reduced Form Evidence

In this section we lay out several facts to begin characterizing marginal consumers with respect to subsidy across two dimensions: previous vehicle ownership and income. The section concludes with a back-of-the-envelope calculation of how much fleet emission could be reduced by subsidy.

We conduct two sets of reduced form exercises. The first rely on stated preferences on vehicle purchase behavior in the California Vehicle Survey. The advantage in using this survey is the inclusion of respondent demographics, in particular income brackets. The survey allows us a first estimation of price sensitivities across different income groups without relying on aggregated demographic statistics. The second set of exercises makes use of the IHS registration data to study replacement behavior.

## 4.1 Subsidy Impact on EV Purchases and Emissions

### Stated Preference Model

The CVS provides four sets of information on households. The first are vehicle details, such currently owned vehicle type (compact, SUV, etc.), fuel type (gasoline, PEV, PHEV, etc.), vintage, and mpg. The second are demographics, previously described. The final two are more valuable features for the exercise here, including a statement of the participants' most preferred vehicle for the next purchase in terms of vehicle type, fuel type, vintage, and her willingness-to-pay.

The estimation itself will depend on vehicle choice experiments, the last of these features. Each survey participant is given eight hypothetical choice sets, each of which has four vehicle choices. See Figure A.3 for a sample choice set. For each choice set, one reference vehicle model is generated, matching the participants stated preference for vehicle type, fuel type, vintage, and willingness-to-pay in their next purchase. The rest three choices in each choice set are randomly generated with disproportionate probabilities on vehicles similar to the reference model.

Characteristics of the choices are randomly at around the mean attributes of vehicles, conditional on the vehicle type, fuel type, and vintage. Price is adjusted by the willingness-to-pay for the reference vehicle. In the estimation, we control for the stated vehicle type, fuel type, and vintage choices so that prices and other characteristics are completely random conditional on those variables. Excluding survey participants with some missing values leaves us with 3,405 households and a total 27,240 experiments, 8 for each household.

Because the experiment choice set does not include an outside option, we set up a model of "inside" demand. For household $i$ the utility of purchasing car $j = 1, \ldots, 4$ is given by

$$u_{ij} = \alpha_i p_{ij} + P'_{ij}\alpha_i^p + p_{ij}P'_{ij}\alpha_i^P + X'_j\beta_i + z'_i\pi_{ij} + \varepsilon_{ij} \tag{2}$$

Each choice 14 attributes $X_j$ which is exact information given to the household (see Figure A.3). The vector $z_i$ summarizes each household. Each household is defined by 11 characteristics — their income, household size, implied Federal Poverty Level (FPL), currently owned vehicle's type, fuel type, vintage, mpg, and whether the owner plans to scrap the vehicle, in addition to the reference vehicle type, fuel type, vintage, and willingness-to-pay for the reference vehicle.[10] Finally, the availability of charging stations, the amount of time in minutes to reach the closest EV refueling location, is included in $z$. Prices $p_{ij}$ in the model are baseline prices less the incentive included in the survey. We allow price coefficients to vary depending on how luxurious (expensive) the car is. $P_{ij}$ is a three by 1 vector of dummies indicating car's price range – luxury ($\geq$ \$40K), middle (between \$22.1K and \$40K), or non-luxury (below \$22.1K). $\alpha_i^p$ differentiates price sensitivity based on this luxuriousness. For example, price slope for a luxury car is $\alpha_i + \alpha_i^{p,luxury}$. $\alpha_i^P$ indicates

[10] Reference vehicle type, fuel type, vintage, and willingness-to-pay are included in $z$ to control for the mean at which the vehicle characteristics are randomized.

preference to luxury vs non-luxury cars.

To motivate the purchasing probabilities induced by this set up, consider a two-layer nested logit demand system with $0 < \lambda \leq 1$ where nest $n$ is conditional on purchasing a car and nest $m$ is not purchasing a car. The probability of consumer $i$ purchasing product $j$ our demand model induces is already conditional on nest $n$.

### Income Sensitivity Results

We estimate the stated preference model in Equation 2 via maximum-likelihood separately for each of 5 income groups. Table 4.1 summarizes price sensitivities by income group across luxuriousness of a car. In general, price sensitivity to non-luxury cars is at least 10 times higher than to luxury cars, regardless of income.

For non-luxury products, low income consumers are more sensitive to price than high income, as is typically expected. On the other hand, for luxury cars, high income consumers are more price sensitive.[11] Should a policy maker set subsidies based not only on efficiency but expense of a target vehicle, the result hints that subsidies to non-luxury cars targeting low income households would generate the largest change in EV purchasing probability.

Table 4.1: **Price Coefficients by Income Group, Without the Outside Option**

| Income Group | Non-Luxury | Middle | Luxury |
|---|---|---|---|
| Less than $49,999 | -0.0531 | -0.0320 | -0.0010 |
| $50,000 to $74,999 | -0.0369 | -0.0344 | 0.0062 |
| $75,000 to $99,999 | -0.0603 | -0.0314 | -0.0045 |
| $100,000 to $149,999 | -0.0447 | -0.0203 | -0.0094 |
| $150,000 or more | -0.0172 | -0.0307 | -0.0093 |

*Notes:* Cutoffs for the vehicle quality designations are based in price: luxury ($\geq$ $40K), middle (between $22.1K and $40K), or non-luxury (below $22.1K).

Some of the major coefficients are in Table (4.2). The first two columns summarizes the preferences for luxury versus non-luxury vehicles by income group. Luxury cars are less preferred compared to non-luxury cars regardless of income. However, high income consumers have higher taste for luxury cars compared to low income — the difference between non-luxury and luxury cars is much larger for low income. This implies that the share of luxury cars for high income is higher than the share for low income. On the other hand, the share of non-luxury cars for low income is higher than the share for high income.

Combining the finding on preference for luxury versus non-luxury cars with the price sensitivity above, we can draw the demand curves of high income and low income as shown in Figure (4.1).

[11] This result implies that high income household's demand is less convex than a low income household's.

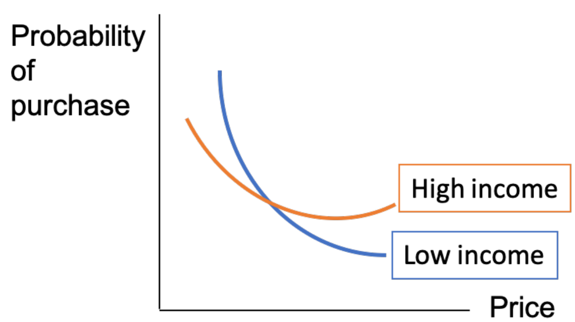
Table 4.2: **Average Preference over Vehicle Characteristics, by Income Group**

| Income | Middle | Luxury | PHEV | PEV | MPGe | Used |
|---|---|---|---|---|---|---|
| Less than $49,999 | -0.4361 | -1.8119 | 0.1429 | 0.1117 | 0.0114 | -0.1589 |
| | (0.2580) | (0.2572) | (0.2110) | (0.2684) | (0.0027) | (0.0745) |
| $50,000 to $74,999 | 0.0922 | -1.6942 | 0.0657 | -0.0599 | 0.0105 | -0.0981 |
| | (0.3145) | (0.3079) | (0.2310) | (0.3144) | (0.0032) | (0.0851) |
| $75,000 to $99,999 | -0.6633 | -1.7907 | 0.4460 | 0.4476 | 0.0081 | -0.3324 |
| | (0.3441) | (0.3575) | (0.2020) | (0.3113) | (0.0028) | (0.0869) |
| $100,000 to $149,999 | -0.5328 | -1.1651 | 0.2173 | 0.2967 | 0.0086 | -0.2791 |
| | (0.3011) | (0.2915) | (0.1854) | (0.2462) | (0.0026) | (0.0747) |
| $150,000 or more | 0.3128 | -0.6807 | 0.4460 | 1.2210 | 0.0026 | -0.3209 |
| | (0.3907) | (0.3697) | (0.1750) | (0.2464) | (0.0027) | (0.0841) |

*Notes:* Cutoffs for the vehicle quality designations are based in price: luxury ($\geq$ $40K), middle (between $22.1K and $40K), or non-luxury (below $22.1K).

The slope is the steepest on non-luxury products for low income consumers. We can conjecture that new EV demand would increase most for subsidies spent on low income consumers when buying non-luxury EV products (e.g. Nissan Leaf or Chevrolet Bolt). The most inelastic part of the demand is at luxury cars for low income, implying that subsidy on luxury cars (e.g. Tesla) for low income is unlikely to increase new EV demand. The implied elasticities are reported in Table A.4 in the Appendix.

Figure 4.1: **Demand Curve by Income Group**




*Notes:* These demand curves are drawn based on the price coefficients and the level of demand in Table A.2 in the Appendix.

To confirm the conjecture that subsidies on non-luxury EVs for low income consumers is most cost effective in increasing in EV demand, we simulate the change in purchasing probability when a $1,000 subsidy is given on new EVs regardless of income. Table 4.3 shows the increment in demand due to the subsidy. Indeed, we find that $1,000 subsidy to low income when purchasing a new non-luxury EV increases total EV demand the most. Subsidies on luxury cars have little impact on demand across income groups.

Table 4.3: **The Change in New PEV Purchasing Probability given $1,000 subsidy**

| Income | Non Luxury | Middle | Luxury | Overall | N |
|---|---|---|---|---|---|
| Less than $49,999 | 0.0098 | 0.0055 | 0.0001 | 0.0028 | 780 |
| | (0.0030) | (0.0021) | (0.0001) | (0.0034) | |
| $50,000 to $74,999 | 0.0054 | 0.0047 | -0.0006 | 0.0018 | 637 |
| | (0.0026) | (0.0026) | (0.0005) | (0.0032) | |
| $75,000 to $99,999 | 0.0070 | 0.0035 | 0.0005 | 0.0021 | 598 |
| | (0.0044) | (0.0024) | (0.0004) | (0.0027) | |
| $100,000 to $149,999 | 0.0084 | 0.0036 | 0.0013 | 0.0026 | 751 |
| | (0.0024) | (0.0012) | (0.0006) | (0.0021) | |
| $150,000 or more | 0.0003 | 0.0004 | 0.0001 | 0.0002 | 639 |
| | (0.0009) | (0.0016) | (0.0004) | (0.0011) | |
| J | 975 | 6042 | 8859 | | |

*Notes:* N is the number of households in each income group. J is the number of vehicle simulated in the survey, tabulated by the luxuriousness of a car. The experiment estimates the change in the probability of purchasing an EV, conditional on its quality, from the provision of a $1,000 subsidy.

Results so far suggest the cheapest way to encourage new EV purchases is to subsidize non-luxury EVs for low income. Whether this is the cheapest method by which to reduce emissions, however, does not immediately follow because of the substitution channel. Table 4.2 highlights the tensions. Column "PHEV" and "PEV" in Table 4.2 shows that high income prefers EVs more. Meanwhile the MPG result suggests high income would substitute away from dirty gas cars to EVs whereas low income would substitute away from relatively clean gas cars to EVs. In other words, preference for MPG is much more convex for high income. This creates a contradicting force in determining the marginal consumers on emission reduction.

Table 4.4: **Average MPG Improvement from a $1,000 EV Subsidy**

| Income | MPG | MPG (Gas) | No Subsidy | Subsidy | Delta | % Delta | N |
|---|---|---|---|---|---|---|---|
| Less than $49,999 | 25.8910 | 24.6031 | 36.1626 | 36.8486 | 0.6860 | 0.0195 | 27240 |
| | (12.3401) | (8.7106) | (13.6814) | (13.8731) | (0.4286) | (0.0101) | |
| $50,000 to $74,999 | 26.9780 | 24.4920 | 35.6366 | 36.0716 | 0.4350 | 0.0126 | 27240 |
| | (16.2177) | (11.1071) | (14.8270) | (14.9598) | (0.3320) | (0.0079) | |
| $75,000 to $99,999 | 28.4716 | 25.1505 | 36.8124 | 37.2643 | 0.4519 | 0.0132 | 27240 |
| | (16.0691) | (9.5496) | (16.2987) | (16.3906) | (0.3449) | (0.0092) | |
| $100,000 to $149,999 | 29.0905 | 24.0851 | 36.4537 | 36.9855 | 0.5318 | 0.0150 | 27240 |
| | (20.9050) | (9.5111) | (14.2698) | (14.4158) | (0.2973) | (0.0070) | |
| $150,000 or more | 30.7308 | 24.2725 | 35.9330 | 35.9694 | 0.0364 | 0.0010 | 27240 |
| | (22.9981) | (10.4535) | (21.2696) | (21.2813) | (0.1432) | (0.0036) | |

Finally, we compare fuel efficient gains across income when a subsidy is given to new EVs, taking into account of price sensitivity and preference for EV and fuel efficiency. The "no subsidy" column is the expected MPG of a new car (probability of a choice times mpg of the choice) without subsidy. "subsidy" column is the averaged MPG given $1,000 subsidy to new EVs. The difference in these two is the expected MPG improvement due to subsidy. Regardless of subsidy, the MPG improvement is most prominent for low income consumers. It is consistent with the finding that low income consumers prefers high fuel efficiency more than high income as shown in Table (4.2). High income's current cars are already relatively clean on average (mainly because some of them have already purchased EVs) and have low preference for MPG, leading to a smaller improvement in fuel efficiency by replacing their old cars. The effect of subsidy on emission reduction ("delta" column) is in general small, only about 1-2% improvement ("% delta") although reduction of emission by low income is twenty times larger than by high income. Ultimately, we find that low income's high price sensitivity dominates, and therefore, a subsidy is more effective for low income consumers in reducing emission.

Intuitively it is sensible that the price sensitivity of low income dominates the substitutional effect of high income — the substitution effect on the change in MPG is fairly small. If a subsidy can sway high income to substitute dirty gas cars to EVs, the MPG gains would be about 90 on average. On the other hand, if low income substitutes clean gas car to EVs, the MPG gains would be about 80, not enough to dominate the role of price sensitivity.

## 4.2 Subsidy Impact on Vehicle Replacement

### Stated Preference Model

The CVS survey does not give us information on replacement probability. Therefore, we turn to using the realized new car purchase data from IHS. We approximate the vehicle replacement probability by the new car purchase probability. We identify the effect of subsidy on new car purchases.

As detailed in Section 3, an advantage of the California subsidy scheme is the wide variation spatiotemporally from local-based incentive program. Our empirical strategy is to exploit these spatial discontinuities in subsidy levels, following a technique similar to Shapiro (2018). For example, two households with the identical income level living at neighboring ZIP codes are treated with different amounts of subsidy. The identification assumption is that the different EV demand between the bordering ZIP codes is generated from the differences in subsidy. The idea is identical to the standard regression discontinuity — neighboring zip codes are very similar to each other other than the magnitude of treatment.

Subsidy discontinuities along zip code border provides a convenient identification strategy for the demand model. First of all, our level of spatial unit is very granular, unlike other papers using spatial discontinuity as their identification, such as country, state, or county. In addition, as discussed in Section 2, the total amount of subsidy consists of multiple subsidy programs each of which is based on different geographic units. Thus subsidy borders do not necessarily coincide with any pre-existing borders, such as county or air district. Moreover, it is highly unlikely that households would move to a different zip code to take advantage of modest differences in these EV subsidies.

Each border consists of a neighboring zip code pair. We consider each border as one experiment in each quarter and for each income group. The experiment is that one ZIP codes is eligible for X amount of subsidy whereas the other ZIP code is eligible for Y amount of subsidy. As in Shapiro (2018), we only include ZIP codes with a neighboring ZIP codes which has different subsidy to ensures that the ZIP codes bordering one another are considered as controls for each other. The observation is vehicle model-border-ZIP code-year-quarter level where vehicle model is a combination of make, model, and model-year. Estimation is similar to difference-in-differences. We use border fixed effects to control for local-specific characteristics. We also include year-quarter fixed effects to control for the general time-trend in California. We include extensive ZIP code characteristics to control for the potential difference in characteristics within a border pair.

**Robustness and Projected Changes in Replacement**

First, we regress the number of new car purchases on price, subsidy, income, interaction of those, zip code characteristics, and vehicle characteristics. These first results affirm the findings from the stated preference exercises.

Equations 3 and 4 detail the first The left-hand side variable $Y_{tz}$ is the number of new car purchases in time $t$ at zip code $z$.

$$\begin{aligned} Y_{tz} = &\beta^I I_{tz} + \alpha^{pev} pev_{tz} + \alpha^{phev} phev_{tz} + pev_{tz} I_{tz} \gamma^{pev'} + phev_{tz} I_{tz} \gamma^{phev'} \\ &+ Z_{tz}\phi' + FE_z + FE_t + \varepsilon_{tz} \end{aligned} \tag{3}$$

$I$ is either yearly median income in a zip code itself or the vector of income dummies. $\beta$ measure the replacement probability (or new car purchase probability) by income. $pev$ and $phev$ are the subsidy for PEV and PHEV, respectively, derived at the median income. Each $\gamma$ is a vector, corresponding to the derivative of replacement probability with respect to subsidy for each income group. Constant $\gamma$ across income groups imply that the effect of subsidy on car replacement does not by income.

$Z$ includes a list of zip code characteristics, such as the population density, the average percentage of green party voters, weighted by block population, the average number of charging stations (either public or private) within one-mile radius from a census tract centroid within the zip code, weighted by population in the tract, the average charging stations at tracts where people work. In addition, fixed effects for zip codes and year-quarters are included.

Rather than using a full sample of zip codes, we also try using "border" zip codes with border-pair fixed effects instead of zip code fixed effects, $FE_p$. For each pair of zip codes $p$,

$$\begin{aligned} Y_{tpz} =& \beta^I I_{tpz} + \alpha^{pev} pev_{tpz} + \alpha^{phev} phev_{tpz} + pev_{tpz} I_{tpz} \gamma^{pev'} + phev_{tpz} I_{tpz} \gamma^{phev'} \\ &+ Z_{tz}\phi' + FE_p + FE_t + \nu_{tpz} \end{aligned} \tag{4}$$

Since $Y$ can be zero, we estimate the equation above by assuming that $Y$ follows Poisson distribution with population as an exposure. We use ACS survey's classification on income – below \$15K, 15-25K, 25-35K, 35-50K, 50-75K, 75-100K, 100-150K, 150-200K, and above 200K. The first column in Table 4.5 shows the coefficients using the entire zip code and the second column shows border zip codes only. The results are almost identical to each other. Incidence ratio will be exponent of the coefficient. Standard errors are clustered at the county level. 35K is one if the median income in a zip code at the time t is greater than or equal to \$35K but less than \$50K and zero otherwise. The rest of the income group dummies follow similarly.

Table 4.5: Number of Total New Purchases

| | (1) | (2) |
|---|---|---|
| | All Zip Codes | Border Zip Codes |
| Density | -0.0819 | -0.0281 |
| | (0.0529) | (0.0052) |
| Green | -0.6824 | -0.0814 |
| | (0.4858) | (0.2569) |
| PEV Subsidy | -0.0552 | -0.0001 |
| | (0.0226) | (0.0430) |
| PHEV Subsidy | 0.0577 | -0.0225 |
| | (0.0370) | (0.0662) |
| Home Chargers | -0.0014 | 0.0004 |
| | (0.0007) | (0.0009) |
| Work Chargers | 0.0010 | -0.0017 |
| | (0.0009) | (0.0026) |
| 15K | -1.3170 | 2.6207 |
| | (0.5894) | (1.4828) |
| 25K | -1.2430 | 1.6493 |
| | (0.6956) | (1.4445) |
| 35K | -0.9790 | 1.1035 |
| | (0.6553) | (1.3570) |
| 50K | -1.0665 | 0.5144 |
| | (0.6511) | (1.4442) |
| 75K | -0.8920 | 0.3490 |
| | (0.6389) | (1.4228) |
| 100K | -0.7983 | -0.4242 |
| | (0.6444) | (1.4291) |
| 150K | -0.7044 | 0.8491 |
| | (0.6509) | (1.3255) |
| 200K | -0.7051 | 0.8351 |
| | (0.6506) | (1.3259) |
| 10K subsidy | -0.0079 | 0.0002 |
| | (0.0276) | (0.0665) |
| 15K subsidy | 0.0370 | -0.1136 |
| | (0.0109) | (0.0366) |
| 25K subsidy | 0.0324 | -0.0594 |
| | (0.0098) | (0.0130) |
| 35K subsidy | 0.0183 | -0.0278 |
| | (0.0081) | (0.0137) |
| 50K subsidy | 0.0251 | 0.0044 |
| | (0.0055) | (0.0129) |
| 75K subsidy | 0.0148 | 0.0180 |
| | (0.0054) | (0.0130) |
| 100K subsidy | 0.0077 | 0.0707 |
| | (0.0079) | (0.0176) |
| cons | -2.4928 | -4.8360 |
| | (0.7778) | (1.3114) |
| N | 15644 | 29057 |

The robustness check largely validates the qualitative stated preference findings. The average

Table 4.6: **Subsidy Impact on Vehicle Replacement Probability**

| | Number of Transactions |
|---|---|
| Subsidy | 0.0261 |
| | (0.0544) |
| 25K*subsidy | 0.3124 |
| | (0.0944) |
| | ... |
| 100K | -0.1574 |
| | (0.0337) |
| | ... |
| Intercept | -2.9740 |
| | (1.6502) |
| N | 29057 |

elasticity is $-2.42$.[12]. The price coefficient indicates that a thousand dollar subsidy increases EV demand by 8.8% ($e^{0.0923}-1$). On average, preference for gas and PEV are not significantly different, although PHEV is less preferred. As income goes up, consumers value EVs more. For example, income group of 75K-100K is about four times more likely to purchase PEV ($e^{-0.5518+1.8971}$) compared to the group of below 25K. This result is consistent with CEC 2017 transportation survey. Finally, we find that high income consumers are less price sensitive than low income consumers, confirming the findings in the literature. Average price elasticities for income group 25-35K is -2.22 whereas it is -1 for 75-100K group, given the average vehicle price. A thousand dollar subsidy for 25-35K increases EV demand by 7.8%, implying that 93% of the consumers in this group are inframarginal. A thousand dollar subsidy for 75-100K increases EV demand by 3.4%, also implying that 97% of the consumers are inframarginal. This finding is consistent with Chen, Hu and Knittel (2017) which find that about half of the consumers are inframarginal consumers.

To put these data to use on replacement, we run a simple model of the number of transactions — used plus new — on the subsidy level interacted with a set of income brackets. The abbreviated results are reported in Table 4.6. The impact of a $1,000 subsidy is higher for lower income consumers than higher and then only a moderate change in 0.05 percent probability of replacing their current vehicle with a new used or car to a 0.07 percent probability.

# 5 Conclusion

These exercises are the first step in estimating a more complete model of consumer responsiveness to electric vehicle subsidies and, in turn, the impact of these subsidies on fleet vehicle emissions. A full picture requires accounting for both the substitution effect of the subsidy and the replacement impact, that is what vehicles are being replaced when a new vehicle is purchased and what happens to the old vehicle.

[12]Calculated from $= (exp(-0.0923) - 1) * 27.466$ where the average price is $27466

The results so far affirm the picture of substitution supported in recent research that minimizing the dollar per reduced unit of vehicle emission requires targeting lower income consumers. Additionally, our final reduced form exercise suggests that replacement behavior also works in favor of targeting lower income consumers. These consumers have the highest external margin for replacement behavior.

The final descriptive piece to study is what vehicles are actually being replaced and the impact of the subsidies on the quality and frequency of scrapping, the only means by which to remove lower fuel efficiency vehicles from the road. We leave this to continued work on this project along with the full structural model, in the vein of Schiraldi (2011), which can decompose the contribution of the different channels on the social fleet emissions benefit of targeting various consumers with EV incentives.

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# A Supplementary Information

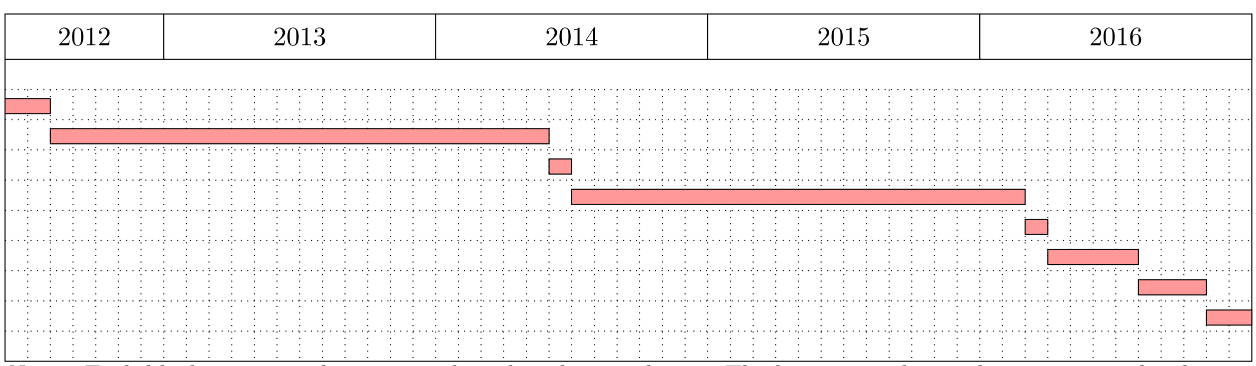
## A.1 Figures and Tables

Table A.1: **List and Characteristics of EVs Available in Q4 2013 in California**

| Make | Model | PHEV | Price (MSRP) | Range[a] | Miles / $[b] |
|---|---|---|---|---|---|
| Chevrolet | Spark EV | | $26685 | 81.94 | 24.80 |
| Nissan | LEAF | | $28880 | 72.98 | 20.70 |
| FIAT | 500e | | $31800 | 87.01 | 24.02 |
| Smart | ForTwo Electric Drive | | $25000 | 76.05 | 22.62 |
| Chevrolet | Volt | YES | $39145 | 380 (38) | 20.22 |
| Honda | Fit EV | | $36625 | 81.98 | 24.88 |
| Ford | Focus Electric | | $39200 | 75.95 | 20.17 |
| Toyota | Prius Plug-In Hybrid | YES | $29990 | 540 (11) | 10.03 |
| Ford | CMAX Energi | YES | $35340 | 550 (20) | 18.42 |
| Toyota | RAV4 EV | | $49800 | 102.87 | 15.82 |
| Honda | Accord Plug-In Hybrid | YES | $32000 | 570 (13) | 23.97 |
| Tesla | Model S | | $69900 | 209.12 | 19.13 |
| Average | PEV | $36947 | 235.66 (72.49) | 20.40 | |
| Average | Gas (Top 70%)[c] | 0.0155 | $27656 | 439.27 | 6.68 |

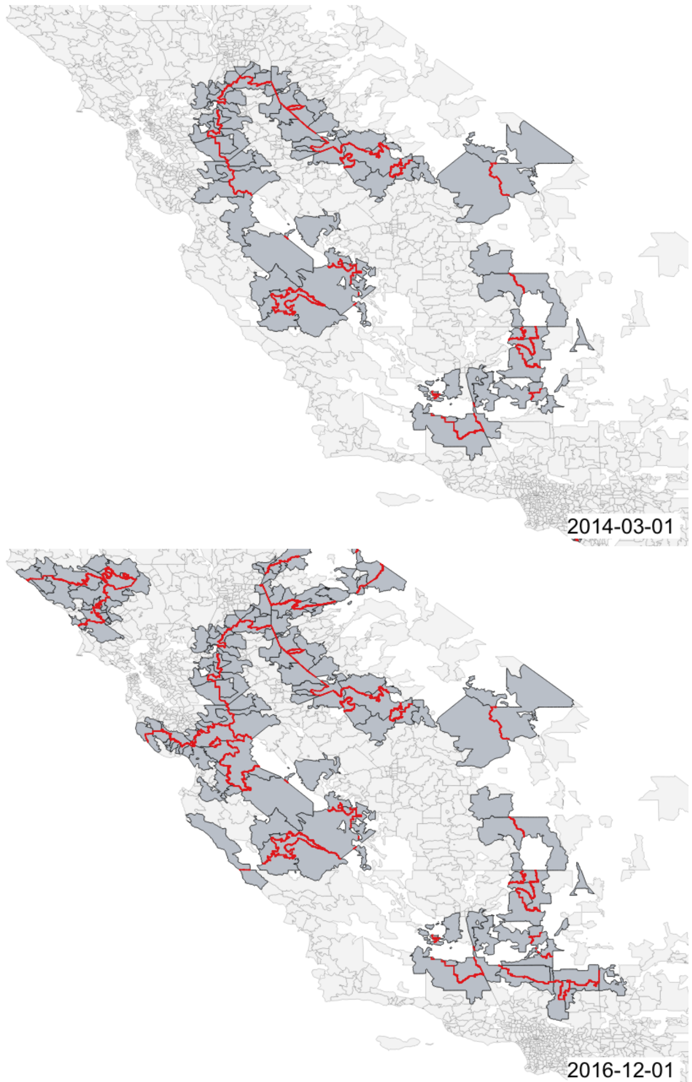
*Notes:* Vehicles covered are those eligible for the Clean Vehicle Rebate Project rebate in Q4 2013.
[a] For PHEVs electric drive range is in parentheses.
[b] Miles per dollar (MP$) is calculated assuming average Time of Use rate offered by utility companies in California. Miles per gallon for PEVs is substituted by MPGe, which uses the equivalency 33.7kWh = 1 gallon.
[c] We only took the list of gas vehicles within the top 70% of the market share.

Figure A.1: **Local Plug-in Electric Vehicle Subsidy Timeline**




*Notes:* Each block corresponds to a month within the noted year. The line moves down whenever a new local subsidy program for PEVs is introduced in the state.

Figure A.2: **Zip Code Tabulation Areas on Policy Boundaries, in 2014 and 2016**




*Notes:* The smallest geograhpic units are zip code tabulation areas. The red line indicates a boundary at 1) where EV subsidies change and 2) tabulation areas are wholly on either side of a policy boundary. The Beverly Hills, zip code 90210, example from Section 2 would not be considered a boundary because different subsidy programs are available in different parts of the zip code. These borders were calculated for a person with an income between \$50,000 and \$75,000.

Figure A.3: Sample Vehicle Choice Set

Please carefully review each vehicle and all its features below. Assuming these are the only vehicles available to you to purchase, **please select the ONE vehicle you would most likely purchase.**

| Vehicle Choice 1 | Vehicle A | Vehicle B | Vehicle C | Vehicle D |
|---|---|---|---|---|
| Vehicle Type | Midsize car | Pick-up truck, small | Van, small | Midsize car |
| Fuel Type | Hybrid (Gasoline) | Full Electric Vehicle | Compressed Natural Gas (CNG) vehicle | Gasoline-ethanol Flex Fuel vehicle (E85 FFV) |
| Vehicle Models Available | 19 | 4 | 2 | 21 |
| Model Year | Used (2014) | New (2016) | New (2016) | Used (2012) |
| Vehicle Price | $12,300 | $23,400 | $17,400 | $7,300 |
| Purchase Incentive | None | HOV Access | None | None |
| MPG / Fuel Economy | 34.2 | 76.2 | 26 | 26.8 |
| Fuel Cost per 100 miles | $5.11 | $11.00 | $22.08 | $7.95 |
| Refueling Station (Time is takes to get to this type of station) | Refuel at station (10 min) | Plug-in at work (0 min) | Refuel at "fast fill" station (15 min) | Refuel at station (3 min) |
| Refueling Time | 5 min | 8 hours | 3 min | 8 min |
| Vehicle Range | 487 miles | 150 miles | 150 miles | 442 miles |
| Trunk/Cargo Space | 16 cubic feet (4 suitcases) | 9 cubic feet (2 suitcases) | 20 cubic feet (5 suitcases) | 15 cubic feet (3 suitcases) |
| Annual Maintenance Cost | $446 | $468 | $473 | $387 |
| Acceleration Rate (0-60 mph) | 10.3 secs | 9.5 secs | 5.9 secs | 9.5 secs |
| Select One: | ○ | ○ | ○ | ○ |

Source: California Vehicle Survey

Table A.2: **Level of Demand**

| Income | Non Luxury | Middle | Luxury | N |
|---|---|---|---|---|
| Less than \$49,999 | 0.2991 | 0.2588 | 0.1909 | 780 |
| | (0.1603) | (0.1584) | (0.1332) | |
| \$50,000 to \$74,999 | 0.2938 | 0.2742 | 0.1759 | 637 |
| | (0.2519) | (0.2553) | (0.1975) | |
| \$75,000 to \$99,999 | 0.2700 | 0.2387 | 0.2453 | 598 |
| | (0.2999) | (0.2820) | (0.2780) | |
| \$100,000 to \$149,999 | 0.2819 | 0.2728 | 0.1893 | 751 |
| | (0.1906) | (0.1986) | (0.1634) | |
| \$150,000 or more | 0.2449 | 0.2378 | 0.2709 | 639 |
| | (0.4147) | (0.4106) | (0.4326) | |
| J | 32221 | 43475 | 33264 | |

*Notes:* N is the number of households in each income group. J is the number of vehicle simulated in the survey, tabulated by the luxuriousness of a car. The reported elasticities are elasticities conditional on purchasing a car. They appear larger than -1, which is a natural implication of logit-type demand when there is no outside option. Therefore, the reported elasticities should not be interpreted as inelastic. Let $s_{j|n}$ be the conditional probability of purchasing $j$ given purchasing a car and let $s_j$ be the unconditional probability. What we report, the conditional elasticity of product j given purchasing a car (of nest n), is $-\alpha(1-s_{j|n})p_j$. Actual elasticity, the unconditional elasticity of vehicle j, is $-\alpha(\lambda+(\lambda-1)/\lambda s_{j|n}-s_j)p_j$. The actual elasticities are always more negative as long as the probability of not purchasing a vehicle is positive. Nonetheless, the order of elasticities across income is preserved.

Table A.3: **Used EV Sales Shares by Income Category, Q4 2016**

| Type | Income | Q4 2016 Used Sales Share | Q4 New Share |
|---|---|---|---|
| PEV | Less than $49,999 | 0.0011 | 0.0083 |
| | $50,000 to $74,999 | 0.0024 | 0.0155 |
| | $75,000 to $99,999 | 0.0046 | 0.0256 |
| | $100,000 to $149,999 | 0.0089 | 0.0520 |
| | $150,000 or more | 0.0154 | 0.0759 |
| PHEV | Less than $49,999 | 0.0219 | 0.0527 |
| | $50,000 to $74,999 | 0.0330 | 0.0746 |
| | $75,000 to $99,999 | 0.0482 | 0.0948 |
| | $100,000 to $149,999 | 0.590 | 0.1147 |
| | $150,000 or more | 0.0727 | 0.1313 |

*Notes:* Shares are calculated by dividing the sum of cars of a fuel category sold over all vehicles sold in zip codes with a median income in bracket specified.

Table A.4: **Elasticities by Income Group, Without the Outside Option**

| Income | Non Luxury | Middle | Luxury | Overall | N |
|---|---|---|---|---|---|
| Less than $49,999 | -0.5581 | -0.7059 | -0.0511 | -0.4623 | 780 |
| | (0.2353) | (0.2032) | (0.0221) | (0.3332) | |
| $50,000 to $74,999 | -0.3897 | -0.7446 | 0.3083 | -0.3182 | 637 |
| | (0.1966) | (0.3019) | (0.1437) | (0.4980) | |
| $75,000 to $99,999 | -0.6574 | -0.7103 | -0.2050 | -0.5404 | 598 |
| | (0.3600) | (0.2932) | (0.1142) | (0.3557) | |
| $100,000 to $149,999 | -0.4794 | -0.4399 | -0.4662 | -0.4596 | 751 |
| | (0.2102) | (0.1459) | (0.2231) | (0.1925) | |
| $150,000 or more | -0.1927 | -0.6939 | -0.4069 | -0.4581 | 639 |
| | (0.1288) | (0.3968) | (0.3060) | (0.3743) | |
| J | 32221 | 43475 | 33264 | | |

*Notes:* N is the number of households in each income group. J is the number of vehicle simulated in the survey, tabulated by the luxuriousness of a car. The reported elasticities are elasticities conditional on purchasing a car. They appear larger than -1, which is a natural implication of logit-type demand when there is no outside option. Therefore, the reported elasticities should not be interpreted as inelastic (See table notes for Table A.2). The actual elasticities are always more negative as long as the probability of not purchasing a vehicle is positive. Nonetheless, the order of elasticities across income is preserved.

## A.2 Local Subsidy Details and Finding Policy Boundaries

This appendix covers two issues: the construction of the local subsidy data and identification of subsidy policy boundaries.

As detailed in the main text, the California Air Resource Board's *driveclean.ca.gov* allows users to query based on their zip code and receive a list of incentive programs available, among other categories, PHEV and PEV purchases. To the extent this website fully collects the information on these programs is the accuracy of the local program data we have.

To collect the data, we scraped the website by querying over the full list of zip codes in California. The raw query yielded 17 unique local vehicle programs for the time period of interest. Unfortunately, information on vehicle eligibility, program dates, etc. are not easily accessed. To complement the scraped information, we manually determined the coverage area, vehicle and income eligibility, and program dates. For reasons noted in Section 2, we dropped low-income vehicle replacement programs for the analysis so far.

The final piece of constructing the data set was to properly identify the geographic scope of the programs. While the Drive Clean website might indicate zip code 90210 all enjoy a potential EV subsidy from South California Edison, only some of the residents live in that utility district. We linked each program to census tracts based on the true residency requirements for each program. We then aggregated tracts up to zip code tabulation areas and tested what percentage of the population fell underneath an area with common subsidy policies. Only tabulation areas in which at least 90% of the population fell under an area with common subsidy policies are included in any spatial analysis around these incentives.

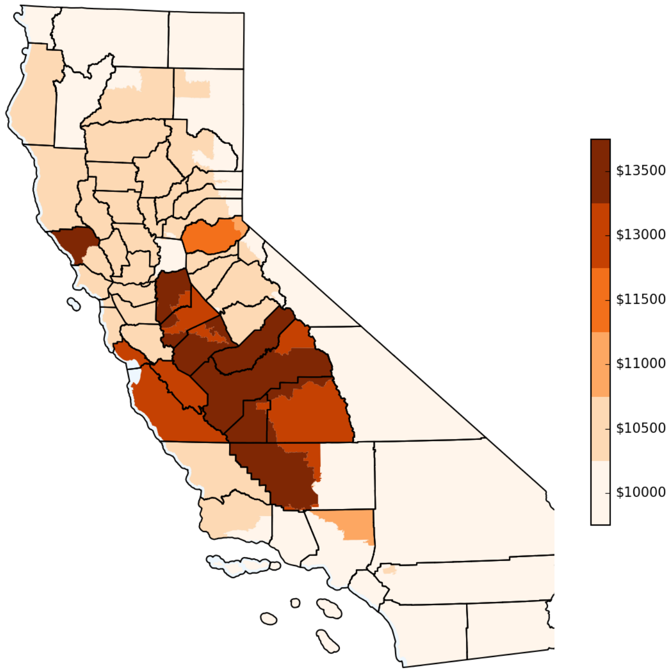
Two complications of our setting are that policy boundaries change over time, and there are potentially multiple policy boundaries at a given time for people of different income groups. Figure A.1 illustrates the pace of these changes. The way these changes manifest, however, is simply the addition of a new boundary over time rather than affecting old boundaries. Importantly, it does not preclude reduced form analysis tracking tabulation areas around a boundary over time. After the period of study, in 2017, new policies introduces start to break part these old policy boundaries, most noticeably in the San Joaquin Valley, as seen in Figure A.4. Income-based eligibility programs are difficult to manage without household-level data outside of a structural model. For now this enourages reading more into the results from the California vehicle survey rather than aggregated IHS data when studying the impact of subsidies across income groups.

## A.3 Additional Data Sources

The next several sections detail the collection and construction of secondary data used in the reduced form analysis and eventually in the structural demand estimation.

One of the most important spatially heterogeneous features affecting EV demand are charging stations. Splintered versions of this research study that relationship directly, as do Li (2017),

Figure A.4: **Plug-in Electric Vehicle Subsidy Available, April 2017**




*Notes:* The subsidy map assumes a person with a $60,000 income is purchasing a plug-in electric vehicle. The coloration denotes maximum available subsidies, assuming full uptake, for a person residing in the area.
*Source:* Local subsidies by zip code are available on driveclean.ca.gov.

Springel (2017), and Zhou and Li (2018) among others. As mentioned in the main text, we collect charging station data from the Alternative Fuels Data Center (AFDC). These data sets provide longitude and latitude coordinates for the stations allowing great flexibility in how we spatially aggregate charging stations for use in the model; more details on this particular point follow in Section A.4. Data on charging station opening dates are provided in older snapshots, pre 2014, of the dataset. In the period since then we deduce openings by assuming stations that appear between snapshots, which we collect twice a week, open in that time frame.[13]

To proxy for political preferences, we classify consumers (or zip codes) into three groups — Republicans, independents, and Democrats — with the latter presumably the most concerned about environmental issues. We use registration data from the Federal Election Commission (FEC) and California Statewide Database to develop a distribution of political tastes by zip code. We treat Democratic, Green, and Peace and Freedom Parties as "green" parties. This data is available by census block and each year. We aggregate the percentage of green voters to the zip code tabulation level by taking an average weighted by the block population.

[13]Operators provide the AFDC with opening dates of new stations, but OCM also relies on "community submissions" which might be less reliable than the information provided by operators. One may also worry OCM stations are consistently reported "late" after there is enough of an electric vehicle community in the area to report the station.

While not relevant for the aggregated reduced form analysis, one concern with individual level data in the structural analysis is the potential correlation between income and political preferences. We simulate this joint distribution with a combination of ACS and FEC data. For most counties in California the ACS annually reports the percent of surveyed households in designated income brackets. Using this information we fit a log-normal income distribution to each county-year used for simulating income. From the FEC we can observe individuals who have donated over $250 to a political action committee (PAC) or to a candidate for a federal election. Using information on the political affiliation of these candidates (or to the political affiliations of the candidates to which the PACs have donated), we associate each individual with a political party based on the largest recipient of their donations. Under the assumption that wealthier individuals donate more to their political causes, we then use this constructed data set to derive a multinomial distribution of three political affiliations (Republican, Democrat, and independent) for several income brackets defined by donation sizes.

We found, however, that it was unreasonable to expect individuals in the lowest income brackets to be donating over $250 to political campaigns. Therefore, we designated a cutoff for wealth above which the FEC data was a good proxy for political affiliation and below which we use average political party affiliations to assign parties. Matching the joint distribution of income and political preference from a survey of California households in Ansolabehere and Pettigrew (2014), we found that a cut off at the median income in the county-year worked best.

Using older data toward the beginning of our sample period, table A.5 provides some descriptive evidence regarding how political preferences and income might affect PEV purchases. The second and third columns in Table A.5 show that more PEVs are sold in high income counties compared to relatively low income counties. This is, of course, a finding we emphasize in the main body of the paper. However, income is not the only factor correlated the PEV purchase behavior. The fourth column reveals that San Francisco, Marin, and Sacramento counties prefer the PEV LEAF over the PHEV Volt while Orange and Riverside prefer Volt over LEAF. A critical difference in the makeup of these counties are political preferences. The former counties tend to have more Democrats than Republicans whereas the latter counties have more Republicans than Democrats.

Table A.5: **Heterogeneous Income and Political Distribution by County**

| County | Income[a] | PEV[b] | LEAF/Volt[c] |
|---|---|---|---|
| Orange | $96,036 | 8.44 | 0.72 |
| San Francisco and Marin | $108,690 | 5.68 | 1.54 |
| Riverside | $69,835 | 2.61 | 0.62 |
| Sacramento | $68,532 | 2.73 | 2.15 |

[a] Average household income in 2013, ACS
[b] Total PEVs sold per 1,000 through August 2014 (using CVRP data)
[c] Leaf/Volt: ratio between Leaf and Volt demand

## A.4 Construction of the Charging Station Variable

Table A.6: **Cumulative Charging Stations in California**

| Year | Quarter | Cumulative Stations | Cumulative Private | Cumulative Public |
|---|---|---|---|---|
| 2010 | 1 | 734 | 364 | 370 |
| 2010 | 2 | 746 | 370 | 376 |
| 2010 | 3 | 752 | 370 | 382 |
| 2010 | 4 | 799 | 373 | 426 |
| 2011 | 1 | 927 | 384 | 543 |
| 2011 | 2 | 1243 | 486 | 757 |
| 2011 | 3 | 1410 | 531 | 879 |
| 2011 | 4 | 1759 | 569 | 1190 |
| 2012 | 1 | 2220 | 657 | 1563 |
| 2012 | 2 | 2770 | 765 | 2005 |
| 2014 | 1 | 4908 | 992 | 3916 |
| 2014 | 2 | 5214 | 1005 | 4209 |
| 2014 | 3 | 5659 | 1056 | 4603 |
| 2014 | 4 | 6355 | 1124 | 5231 |
| 2015 | 1 | 7008 | 1197 | 5811 |
| 2015 | 2 | 7803 | 1319 | 6484 |
| 2015 | 3 | 8792 | 1377 | 7415 |
| 2015 | 4 | 9382 | 1477 | 7905 |
| 2016 | 1 | 10634 | 1686 | 8948 |
| 2016 | 2 | 11294 | 1719 | 9575 |
| 2016 | 3 | 12182 | 1815 | 10367 |
| 2016 | 4 | 12904 | 1862 | 11042 |

*Source:* AFDC
The private and public labels are provided from the AFDC.

Table A.6 tracks the raw number of charging stations we find are deployed before and during the period of study. Using these data we construct two sets of charging stations counts for consumers living in a particular zip code: the public charging stations near that home zip code and an estimate of the charging stations near their work zip code. While home-area zip code charging stations may seem like the most natural measure, home chargers for PEVs appear to mitigate the need for other proximal charging stations.

To assign a count of work charging stations to a home zip code, we use additional information from the Longitudinal Employer Household Dynamics Origin-Destination Employment Statistics (LODES). LODES links workers to employers and further allows us to observe a worker's residential and employer census blocks. Employer location is collected from the Quarterly Census of Employment and Wages (formerly ES-202) and employee residence location is collected from the Composite Person Record by the Census Bureau.[14] See Table A.7 for more information.

We use the information from LODES to determine the relevant work locations for a given home zip code. To construct the count of work charging stations, we weight the number of public charging within a 1-mile radius of the work census block's centroid by the home zip code's population working

[14] See Graham, Kutzbach and McKenzie (2014).

Table A.7: **LODES Residence and Workplace Summary**

| Year | Total People | Unique Census Blocks | | | Unique Zip Codes | | | Distance | |
|---|---|---|---|---|---|---|---|---|---|
| | | Home | Work | Avg. Link[a] | Home | Work | Avg. Link[a] | Mean | Med |
| 2012 | 14.59m | 380564 | 235288 | 1.01 | 1757 | 1742 | 21.26 | 22.85 | 5 |
| 2013 | 15.05m | 380762 | 237490 | 1.01 | 1760 | 1745 | 21.42 | 23.59 | 5 |
| 2014 | 15.47m | 381181 | 240242 | 1.01 | 1758 | 1746 | 18.77 | 26.61 | 5 |
| Total | – – | 397471 | 265663 | 1.01 | 1760 | 1752 | 20.38 | 24.39 | 5 |

*Source:* 2012-2014 Longitudinal Employer Household Dynamics Origin-Destination Employment Statistics (LODES)

[a] Measured as the average number of people in home area commuting to the work area

in that census block. For each home zip code, there are, on average, 11.89 associated work place zip codes. Most home-work zip code links feature few unique households because of the sample size and level of granularity. On average 1.78 households make the trip between the home-work zip code, though some feature as many as 100.