Cash or Charge: Assessing Charging Station Build Out and Incentive Programs' Roles in Electric Vehicles Adoption

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Abstract

This paper assesses the efficacy of several US federal investment projects amounting to $130 million to build out the foundation of an plug-in electric vehicle (PEV) charging network and to encourage purchase of these vehicles. Using a new micro-level data set of electric vehicle purchases in California to estimate a rich discrete choice model of automobile demand, we analyze whether these charging stations have had a significant role in the adoption of electric vehicles in California over the past several years and weigh them against several other policy alternatives. Our initial results suggest that the PEV market share would have declined by 16% without the charging station investment. Alternatively, PEV market share would have declined by only 1.78% without California or federal tax incentives. Of additional interest is the environmental impact of these interventions. By consumers substituting from gas to PEV vehicles through these programs, carbon emissions have thus far been reduced by 15,000 tons per year and 1,650 tons per year, respectively.

The next step in this analysis is to model forward-looking consumers who anticipate the evolution of the network, and to explicitly model the suppliers in this network. We expect our current results underestimate the potential value of the investment project by ignoring the long-term adoption effects of the initial boost in demand.

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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 toward investment and research into electric vehicles. Of this allocation $115 million was specifically designated for the deployment and study of a first-stage charging station network for plug-in electric vehicles (PEVs) across several states. The EV Project and ChargePoint America, the beneficiary projects of this grant, deployed nearly 5000 charging stations in California homes and public locations from May 2010 to the end of December 2013 starting from the approximate 480 in place at the beginning of the period.[1] The federal and California state governments concurrently rolled out other incentive programs to encourage the adoption of electric cars, including hefty rebates, tax credits, and electricity discounts.

We study these developments with a focus on understanding the role these programs actually played in spurring plug-in electric vehicle (PEV) adoption and whether alternative policy choices could have resulted in more favorable adoption outcomes. Our work fits with (1) a growing body of policy research around encouraging PEV purchases and developing a suitable infrastructure for their use to reduce carbon emissions and with economic literature on indirect network effects.

There are numerous policy studies on the rebate programs and deployment of charging network. However, they do not specified how much of the PEV demand is led by the government support. This paper quantifies the portion of PEV market growth attributable to the government support. Furthermore, we suggest the reduced amount of carbon emissions, resulted from substituting gas vehicles with PEVs under the current policy. We also simulate the reduction in carbon emissions under different policies and evaluate the effectiveness of each policy. The results shed light on optimal government support for expansion of PEV sales and reduction in carbon emissions in turn.

Consumers' price sensitivity determines whether the monetary compensation policies are effective in encouraging PEV purchase. We estimate demand for automobile and evaluate the increase in PEV shares due to the rebates. If consumers are highly sensitive to price, then the rebate programs do provide significant incentives to the consumers for purchasing PEVs.

The effectiveness of deploying public charging stations, such as EV Project and ChargePoint America did, depends on the indirect network effect between PEV and charging station

[1] See Table 9 in Appendix C.

markets. Indirect network effects exist when provision of secondary market (charging station market) has spillovers to demand in a primary market (PEV market). In other words, prevalence of charging stations increases the value of PEVs, leading to high demand in PEVs. The paper looks for the presence of and measure the magnitude of PEV charging network's impact on demand for PEVs. If the indirect effect is significant, then the government support on charging station network is effective in spurring PEV market growth

Using a new data set featuring household-level electric vehicle purchase data with detailed geographic and timing information and supplemented with behavioral data from recent studies on electric car adopters, we estimate a rich discrete choice model of demand for the automobile market in California. The data set permits identification of consumer heterogeneity heretofore impossible in the existing literature. The current version of our model, however, is a static setting in which consumers are not forward looking, and the secondary market (charging stations) does not respond to the size of the PEV market. The next version of the paper will feature the first of these two oversights.

The preliminary results from this static setting predict that these incentive programs have had a measurable impact on the demand for PEVs. One key finding from counterfactuals show that PEV market share increases by as much as 1.6% to 7%, depending on the specific car model, with a 1% increase in CA charging stations. However, our estiamtes also show that a larger tax credit program may have been more effective. We found PEV penetration would have been less by .78% without California or federal tax incentives.

We caution, however, that shutting down the feedback between the primary and secondary markets in this static model may understate the magnitude of an indirect network effect from the charging station network. If, in fact, the feedback between the two networks is strong, 1) we miss the lingering impact of the federal charging station program on future electric vehicle demand and 2) we discount the possibility that consumers are waiting for further developments in the network before adopting electric vehicles. For a classically durable good like automobiles, shutting down the ability for consumers to forward look with respect to potential growth in the secondary market is an another significant issue that may understate the importance of the network to consumers.

The paper is organized as follows. In Section 2 we describe specific obstacles for widespread adoption of PEVs and features of consumers and incentives in California that we deemed important to model. Section 3 places our work into the context of the larger indirect network effect literature. Section 4 presents the model of consumer demand and Section 5 the data used to estimate the model. Section 6 presents the moments we use in a GMM estimation

procedure to derive the parameters of the demand model. We outline how features in our data sets allow the estimation procedure to identify the parameters of demand in Section 7. Finally, preliminary results from the estimation of the static model and several simple policy experiments possible under the static model are presented in Sections 8 and 9.

2 The Market for Electric Vehicles in CA

Many peculiarities of both PEVs and California differentiate its market for electric and gasoline-fueled vehicles and make the region ripe for a focus of this study. Here we discuss various obstacles inhibiting the mainstream adoption of electric vehicles, argue that *a priori* the charging station network may have an appreciable impact on demand, and describe particulars of the California market and PEV purchasers.

PEVs can be classified into two categories: one category is full electric, such as Nissan LEAF and Tesla Model S, and the other is plug-in hybrid electric vehicle (PHEV), such as Chevy Volt and Toyota Prius Plug-In Hybrid. PHEV is different from full electric vehicles because it has an option to fuel the car with gasoline and its range with electric battery only is shorter than full electric vehicles.[2] We use PEV to include both fully electric and plug-in hybrid electric vehicles.

2.1 Charging Electric Vehicles

Before delving into obstacles facing the electric vehicles, it is critical to understand how PEVs "fuel" differently than traditional gas vehicles. Fully electric vehicles and plug-in hybrids recharge their electric engine by, surprisingly, plugging into specially designated charging docks. Most of the charging outlets are compatible to any PEV models. The main difference is the charging speed. Technically any standard electric plug (Level 1 charger) can be used to charge a PEV, but current models, even with relatively small batteries, take anywhere from 20 hours to 10 hours to fully charge.[3] These charging times are clearly unreasonable long for a consumer that plans to use their vehicle in daily usage.

The current PEV-specific charging standard is Level 2 chargers, which can fully charge the Nissan LEAF in approximately 8 hours and the Chevrolet Volt in 4 hours. The cost for faster charging time is the necessity of installing a special Level 2 charging port. But,

[2]These details will be elaborated upon later. See Table 2

[3]The Nissan LEAF, a fully electric vehicle, takes about 20 hours to charge and can get 78 miles per charge. The Chevy Volt, a plug-in hybrid, takes 10 hours to charge and travel 38 miles on its electric engine.

Table 1: **Charging Speed by Charger Type**

Charger Type	Vehicle	Level 1	Level 2	DC Fast
Full Charge Time	LEAF	20 hr	8 hr	30 mins[a]
	Volt	10 hr	4 hr	15 mins[a]
Distance with 1 hr of Charge		2-5 mi	10-20 mi	60 mi
Home Installation Fee		Free	∼$1700	N/A

[a]Time for battery to be 80% charged.

these times still amount to an unreasonable wait for a traveler looking to drive beyond the single-charge range of the vehicle. The newest standard attempts to address this concern. The DC Fast charger can charge vehicles in less than 30 minutes.[4] Unlike Level 1 and 2 chargers, DC fast is is only available at non-residential charging stations. See Table 1 for a comparison of the speed standards. Because compared to Level 2 chargers Level 1 chargers are impractical charging solutions for modern electric vehicles, we do not consider them as part of the charging station network in our analysis.

We further classify charging stations into three groups: residential, public, and private. Residential charging outlets are only accessible to the home owner, and we exclude it from charging network market. The public and private charging stations are installed at public parking lots, malls, restaurants, and so on. We refer them to "charging stations."

The lengthy time to charge these vehicles not only poses a convenience problem but also a congestion problem for public charging stations. According to a charging station usage statistics of PEV owners by the EV Project (2014), owners leave their car charging for 6.2 to 7.4 hours on private away-from-home Level 2 chargers and 3.5 to 4.9 hours on public away-from-home Level 2 chargers. If a PEV driver is looking for a public charging station as a solution for a drained battery, the low turnover at these stations decrease the likelihood of finding an open charger. The current version of the paper does not separately identify inconvenience from these two sources.

2.2 Challenges in PEV Adoption: High Price and Range Anxiety

Government support for PEVs has focused on the burden of their high price and the inconvenience from their limited driving range because they are the most common concerns in driving a PEV. Here, we provide descriptive evidence that the consumers indeed face

[4]Tesla also features special charging standards for its own vehicles. Tesla Superchargers are stationed around the country with long-range travelers in mind and boast charging speeds of less than 30 minutes. The company is also testing a "battery swap" program for this stations, which swaps the drained battery in a Tesla with a fully charged battery in less than 90 seconds.

relatively high price and range anxiety. The disutility magnitude of these inconveniences are not identified by the descriptive statistics, and therefore, we model the PEV demand.

High Price

Electric vehicles tend to have higher upfront prices than gas vehicles. In the bottom of Table 2, we compare the average price of PEVs and gas vehicles. The average price of PEVs is more than 33% higher than gas vehicles in 2013. More specifically, 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, while the most expensive gas vehicle among the top 80 CA car models in 2013 cost $52,800.

Another upfront cost in electric vehicle comes from installation of residential charger. According to the Center for Sustainable Energy (2013*a*), an organization responsible for administrating rebates for electric vehicle purchases in CA, 90% of the PEV purchasers installed a residential charger. For the time period of analysis, the permitting and installation cost for these chargers added about $1,700 in the upfront cost of PEVs.

While PEVs have higher upfront costs, they tend to have lower maintenance and fuel costs than gas vehicles. Without discounting future costs or accounting for changes in the price of oil, the maintenance and fuel costs are about $33,728 for gas vehicle, $20,460 for plug-in hybrid electric vehicle, and $19,344 for full electric vehicles purchased in 2013[5]. Under the assumptions that generate those estimates, the PEV is still overall more expensive than gas vehicles.

The cost burden of PEVs is of often a binding constraint when consumers are making their vehicle purchase decision. Two surveys, Center for Sustainable Energy (2013*a*) and **?**, reveal that 90% of the respondents consider the rebate was an important decision factor in purchasing their PEV. Additionally, 50% claimed that subsidy for residential charger was also important to their decision.

[5]The estimates assume 12,400 annual mileage and a 16-year lifespan. Fuel costs for the gas vehicle are calculated based on 26.7 miles per gallon and a gas price of $3.5 per gallon. The fuel cost for PEV is calculated by assuming $0.13 per kWh, taken from the average CA price as of January 2012, and a mileage of 4.42 miles per kWh. The maintenance and repair costs include battery replacement, engine oil change, tire rotation, etc. The assumptions are taken from Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) 2013. Numerous data sources include AFDC Price Report, AEO Report, Argonne National Laboratory, and so on. See User Guide for AFLEET Tool 2013.

Table 2: **List and Characteristics of PEVs Available in Q4 2013 in California**

Make	Model	PHEV	Share[a]	Price (MSRP)	Range[b]	Miles / $[c]
Chevrolet	Spark EV		0.0007	$26685	81.94	24.80
Nissan	LEAF		0.0078	$28880	72.98	20.70
FIAT	500e		0.0038	$31800	87.01	24.02
Smart	ForTwo Electric Drive		0.0009	$25000	76.05	22.62
Chevrolet	Volt	YES	0.0081	$39145	380 (38)	20.22
Honda	Fit EV		0.0002	$36625	81.98	24.88
Ford	Focus Electric		0.0005	$39200	75.95	20.17
Toyota	Prius Plug-In Hybrid	YES	0.0062	$29990	540 (11)	10.03
Ford	CMAX Energi	YES	0.0046	$35340	550 (20)	18.42
Toyota	RAV4 EV		0.0007	$49800	102.87	15.82
Honda	Accord Plug-In Hybrid	YES	0.0002	$32000	570 (13)	23.97
Tesla	Model S		0.0070	$69900	209.12	19.13
Average	PEV		0.0034	$36947	235.66 (72.49)	20.40
Average	Gas (Top 70%)[d]		0.0155	$27656	439.27	6.68

[a] Clean Vehicle Rebate Project rebate data set.
[b] For PHEVs electric drive range is in parentheses.
[c] 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. [d] We only took the list of gas vehicles within the top 70% of the market share.

Range Anxiety

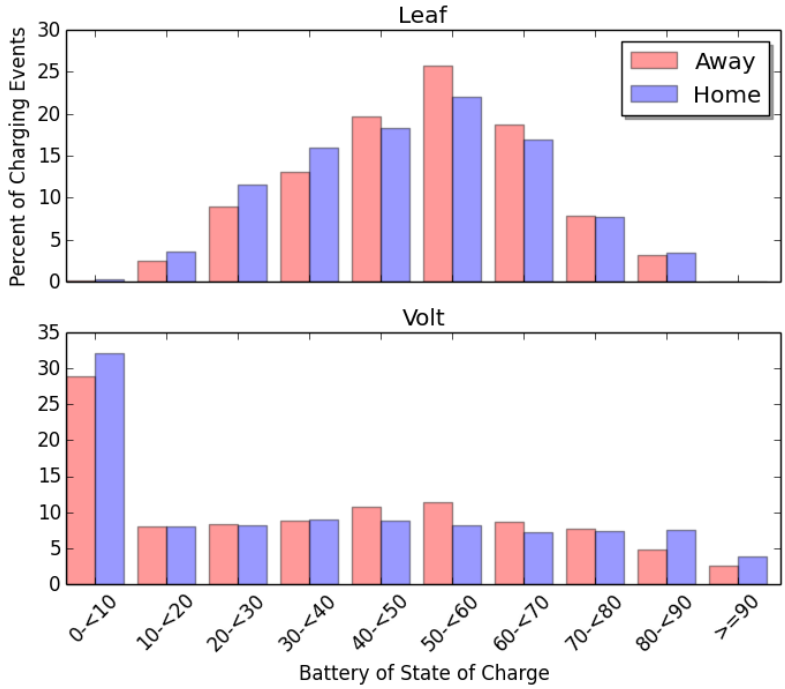
Range anxiety when driving a PEV stems from both their short range and the lack of charging stations. As shown in Table 2, the full electric range of PEVs is on average only 15% of the range of gas vehicles. The Nissan LEAF carries a 72-mile range whereas Honda Civic has more than 400-mile range. The Tesla Model S is the only fully electric vehicle with comparable range to traditional gasoline vehicles. According to the Center for Sustainable Energy (2013*a*), nearly 40% of survey respondents were not satisfied with the electric range of their purchased vehicle (see Table 10in Appendix C).

In addition to the range issue, public electric vehicle charging stations are still lagging far behind the ubiquity of gas stations. In 2013 there were approximately 9,000 gas stations in California compared to 3,000 charging stations. Table 11 in Appendix C describes the number of charging stations over time. While the volume of gas cars is significantly higher, these vehicles do not suffer from either the range problems or extensive filling times that electric vehicles do. According to the Center for Sustainable Energy (2013*a*), 71% of the PEV purchasers were reportedly unsatisfied with the public charging infrastructure (see Figure 2 in Appendix C). Potential PEV buyers then need to remain highly cognizant of charging stations in areas frequently traveled or avoid long trips out of comfortable range entirely.

Because every standard electricity outlet is effectively a charging station, albeit slow,

for an electric vehicle, the importance of a charging station network may not be immediate despite some evidence on the pervasiveness of range anxiety. Further evidence that suggests charging stations should have little impact on demand comes from CA driver habits. The 2010-2012 California Household Travel Survey shows the average Californian drives approximately 38 miles, well within the single-charge range of the Nissan LEAF or Tesla Model S. Table 13 in Appendix C indicates that the drive range for LEAF owners is even shorter (24.8 miles) per day. These figures suggest that charging away from home may be unnecessary for most use cases.

Figure 1: **Distribution of Battery Charge at the Start of Charging Events**



Source: EV Project Electric Vehicle Charging Infrastructure Summary Report, Q4 2013

Other evidence, however, reveals these shorter driving ranges may be a symptom of range anxiety. Table 13 shows that Volt, which has the range of a standard gasoline vehicle, owners tend to use their vehicles lengthier trips. In addition, despite the short trips PEV owners tend to take every opportunity to charge their vehicles. 27% of charging events were away from home for the LEAF while only 16% were for the Volt in Q4 2013 according to EV Project (2014). Additionally, the survey Center for Sustainable Energy (2013*a*) noted the importance of having work-place chargers in their decision to purchase their electric vehicle (see Figure 3).

Even more direct evidence of range anxiety comes from the different charging behavior

between full electric vehicles and plug-in hybrid electric vehicles. Figure 1 reports how much of the battery remains when a charging event takes place, taken from a sample of participants in an EV Project field study (EV Project (2014)). For the range-impaired Nissan LEAF, charging events take place the most when the battery still is 50% full or more. LEAF drivers charge even though the battery is not close to empty. In contrast, the Chevy Volt is charged primarily when the battery is fully exhausted. It reveals that LEAF drivers make a concerted effort to keep the battery at least half full all the time while Volt drivers let them run out. If range were not a concern for LEAF drivers, we should expect to see similar charging event distribution of Volt.

Range anxiety is frequently cited as a key problem facing the widespread adoption of electric vehicles. The immediate solution is the recent trend among car makers to push plug-in hybrid electric vehicles (PHEV) that use an electric drive engine until the power is exhausted and then switches to a traditional gas engine. While still more expensive than traditional gas vehicles, PHEVs provide the comparable range that fully electric vehicles still lack. Table 2 compares the market share, price, and range of the most popular PEVs in California as of Q4 2013.

2.3 Government Incentives Encouraging Adoption

To overcome the challenges in adopting electric vehicles, the federal government, California, and local California governments have all offered varying incentive packages.

Easing High Price

Both California, via the Clean Vehicle Rebate Program, and the federal government offer tax credits for the purchase of PEVs. The federal government offers up to a $7500 for fully electric vehicles, while California offers up to $2500. Some districts in California offer rebates on top of these two programs.[6] Table 3 provides further details on rebate amounts for specific models.

Other monetary incentives include lower electricity rates for charging electric vehicles at home during off-peak hours. Table 12 in Appendix C details potential fuel cost savings from these deals. Additionally, work charging, parking lot charging, and public charging stations typically are offered at nominal to no charge.

[6] Certain counties in the San Joaquin Valley feature rebates up to $3000.

Table 3: **Government Monetary Incentives for PEV**

	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[b]	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 hybird	Zero emission, plug-in hybird
	Lease $\geq$ 36 months	Battery capacity $\geq$ 5Kilowatt-hour
	Battery, Hydrogen Fuel EV	Only battery EV
Total Rebates Issued[c]	35,769	

[a] Plug-in Electric Drive Vehicle Credit (IRC 30D) by IRS
[b] Distributed thus far. FY 2014 - 2015 alone has a new allocation of over $100 million.
[c] As of December 31, 2013.

Easing Range Anxiety

The effort to expand the charging network infrastructure was made by the subsides from the government. In addition to the nearly 2000 charging stations installed in California by ChargePoint America and the EV Project since 2010, over 2500 chargers have been added to the network. They account for 43% of the total charging stations in California as of December 2013. While their origin is not available, representatives of the Department of Energy have suggested many businesses and workplaces have begun installing stations as a convenience to customers or employees. Table 9 in Appendix C has details about the projects.

Other Incentives

The benefits from the programs describe above are included in our analysis. There are some other incentives we do not explicitly model in the paper. For example, limited numbers of PHEVs and fully electric vehicles can gain access to HOV lanes on California highways. To those that have endure Los Angeles traffic, this program could easily be more valuable than any monetary benefit.[7]

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

2.4 Other Relevant Purchase Factors

A survey of vehicle owners who received vehicle rebates from the CVRP Survey reveals that 38%, 18%, and 16% of LEAF, Volt, and Prius Plug-In Hybrid consumers, respectively, were motivated by environmental concerns in the purchase of their vehicles. LEAF, the only zero emission vehicle in that list, purchasers in particular responded that the environment was their biggest motivator. Other than environmental concerns, high income is also a distinctive feature of PEV purchasers. The first panel of Table 14 compares the income distribution of households conditional on vehicle purchase versus PEV purchase. The distribution is skewed more to the right for PEV consumers. More than 50% of the PEV consumers have more than $150,000 annual income.

Because of how important these two demographic features are in distinguishing PEV purchasers from typical vehicle purchasers, we take care to include both in our model of consumers, to be detailed in section 4. To proxy for environmental concern in our estimation and in descriptive analysis of the data, we consider political preferences. Consumers are split into three groups — Republicans, independents, and Democrats — with the latter most concerned with environmental issues. While based on party lines, political preference need not be wholly irrelevant in understanding actual consumption preferences. Costa and Kahn (2013) found liberal communities are more likely to participate in "voluntary restraint", that is consume less electricity than conservative but otherwise identical households.[8]

Table 15 and Figure 6 both provide descriptive evidence regarding how political preferences and income might affect PEV purchase. The second and third columns in Table 15 show that more PEVs are sold in high income counties compared to relatively low income counties. However, income is not the only factor explaining the PEV purchase behavior. The fourth column reveals that San Francisco, Marin, and Sacramento counties prefer LEAF over Volt while Orange and Riverside prefer Volt over LEAF. A critical difference in the make up 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. This is shown in Figure 6. The left panel of contains two wealthy counties (San Francisco and Marin and Orange) but with different average political tendencies. The right panel has two less wealthy counties (Sacramento and Riverside) also with different political preferences. The statistics suggest that income affects the external margin of the PEV purchase decision while political preference may affect which PEV to purchase.

[8] See also Kahn (2007).

3 The Indirect Network Effect Literature

Most recent indirect network literature has emphasized competing platform markets benefiting from the growth of a platform-specific complementary market. Nair, Chintagunta and Dube (2004), Clements and Ohashi (2005), Dubé, Hitsch and Chintagunta (2010), Goolsbee and Klenow (2002), Gandal, Kende and Rob (2000) analyzed the impact of an indirect network effect from software markets in varying tech industries. This line of research differs from our current project in several ways. First, except for Goolsbee and Klenow (2002), thiese papers have featured non-compatible platforms competing for market concentration. In this market, with a few exceptions, charging stations have been standardized to work across all PEVs.[9] Our ultimate question of interest is in the growth of the relatively new electric vehicle market space, rather than competition among firms in a mature market. In this respect our setting is most similar to Goolsbee and Klenow (2002) which analyzes the diffusion of home computers in the 1990s, where the network size and specific tools, like e-mail, drive adoption more than platform-specific software. Additionally, we may consider the role of a similar peer effect in our setting using the methodology proposed by Bollinger and Gillingham (2012) in which the adoption of solar panels is encouraged by neighbors' adoption.

An important feature of market growth in industries with indirect network effects is the feedback mechanism between the main and secondary markets. In this setting if charging stations increase demand for electric vehicles, greater electric vehicle purchases may in turn encourage the growth of the charging station network or eventually turn it to a profitable venture for the private sector. In this static version of the paper, however, we can only present results that shut down the feedback effect between electric vehicle purchasers and charging station placement decision makers. The next step of our analysis which incorporates dynamic decision makers will follow most closely from Gowrisankaran, Park and Rysman (2014) using a technique to tractably model dynamic decision makers in a discrete choice model proposed by Gowrisankaran and Rysman (2012).

The current contributions of this paper to this literature rest in several differentiating factors about our setting. First, a subsample of our observations in the charging station network are free from the typical endogeneity problems borne by the feedback effect. Government-sponsored stations were allocated and predetermined before the electric vehicle market resopnded to their presence. Second, the value of the charging station network features sig-

[9] A notable exception might be Tesla's expanding supercharger network. These chargers are meant for long-distance trips, however, rather than every day use.

nificant heterogeneity depending on the geographic location of consumers; the heterogeneity will prove a valuable source for identification. Third, the setting permits demand that can accommodate heterogeneity in the utility towards the indirect network effect, the notable difference from the setting in Gowrisankaran, Park and Rysman (2014). Hence we do not need to impose that there is a strictly positive or negative relationship between charging stations and demand and can accommodate nuance in tastes for the network currently absent from our model.[10]

4 Demand Specification

In the static model consumers make choices in a specific market m defined by a time q and location g. Our estimation will ultimately consider each county-quarter pair in California a specific market. Let $q(m)$ denote the quarter of market m, and $g(m)$ denote the county of market m. Each consumer has four relevant characteristics: income y, political affiliation d, charging stations within a useful range c, and idiosyncratic tastes $\{\nu\}$ toward specific product characteristics. Let $D_i = (y_i, d_i, c_i, \{\nu_i\})$. Specific details on how we model which charging stations are relevant to consumers is in Appendix B. Consumer i in market m purchases one product from the choice set $J_{q(m)}$ or an outside good to maximize her utility. Note we assume the choice set is fixed across geographic markets in a given time period.

Consumer utility is modeled by a variation on the standard random coefficients discrete choice model. Specifically, consumer i's utility from purchasing a vehicle model j has the following form:

$$\begin{aligned} u_{ij} = \alpha \log(y_i - p_j) + X_j\beta + \sum_{k=1}^{K} X_{jk}\sigma_k\nu_{ik} + PEV_j\left[\beta_e + d_i\beta_d + \sigma_e\nu_{ie}\right] \\ + PEV_j c_i\left[\beta_c + \sigma_c\nu_{ic}\right] + \xi_j + \varepsilon_{ij} \end{aligned}$$

Each vehicle model has $K+2$ observable product characteristics denoted by $W_j = (p_j, X_j, PEV_j)$, where X_j is a vector of K specifications for vehicle j and PEV_j is a indicator variable for plug-in electric or fully electric vehicles. ξ_j is an unobserved (to the econometrician, not consumer) product-specific demand shock, which can be correlated with price p_j, and ε_{ij} is an idiosyncratic preference shock.

[10]For example, we still have not arrived at a convincing proxy for congestion at charging stations. More charging stations are not necessarily better if the usage by other PEV owners is also significantly higher.

This utility model features 2K + 6 parameters of interest $\theta = (\beta', \beta_e, \beta_d, \beta_c, \sigma', \sigma_e, \sigma_c, \alpha)'$. βs are the mean utility derived from a unit of a specific product characteristic, and σs scale the heterogeneity in tastes for each characteristic. We can decompose the utility into components specific to each product, to each consumers, and to PEVs.

$$u_{ij} = \delta_j(\theta) + V_{ij}(\theta) + EV_{ij}(\theta) + \varepsilon_{ij} \tag{1}$$

where

$$\delta_j(\theta) = X_j\beta + \xi_j$$

$$V_{ij}(\theta) = \alpha \log(y_i - p_j) + \sum_{k=1}^{K} X_{jk}\sigma_k\nu_{ik}$$

$$EV_{ij}(\theta) = PEV_j\left[\beta_e + d_i\beta_d + \sigma_e\nu_{ie}\right] + PEV_j c_i\left[\beta_c + \sigma_c\nu_{ic}\right]$$

The terms specific to PEVs are highlighted to emphasize additions to the standard random coefficients model. $[\beta_e + d_i\beta_d + \sigma_e\nu_{ie}]$ captures the utility of purchasing a PEV and may depend on the consumer's political preference. $[\beta_c + \sigma_c\nu_{ic}]$ is the impact of the charging station network on the utility of purchasing a PEV. The magnitude of this term is our measure for the indirect network effect on PEV demand through the charging station network.

Under the assumption that ε_{ij} shocks are iid type-1 extreme value over products and consumers, the probability consumer i in market m purchases vehicle j takes on the familiar logit form.

$$P_\theta(j|W, D_i) = \frac{\exp(\delta_j(\theta) + V_{ij}(\theta) + EV_{ij}(\theta))}{1 + \sum_{j' \in J_{q(m)}} \exp(\delta_{j'}(\theta) + V_{ij'}(\theta) + EV_{ij'}(\theta))}$$

Integrating over all of the individuals in a market yields the aggregate market share. We allow the distribution of individual characteristics to differ by market according to $f_m(y, d, c, \nu)$ but assume the distribution of tastes is $f(\nu)$ is common for all markets and independent from other characteristics. Hence $f_m(y, d, c, \nu) = f_m(y, d, c)f(\nu)$. Finally, we assume that tastes follow a multivariate standard normal distribution with a diagonal variance-covariance matrix. Under these assumptions the market share for vehicle j in market m is

$$S_j^m(\theta|W) = \int P_\theta(j|W, D_i) f_m(y, d, c) f(\nu) d(y, d, c, \nu)$$

The geographic markets we have considered partition California. Within a given time period shares can be further aggregated to the state level by weighting each county with its share of consumers. Let $\pi_q(m)$ denote the fraction of consumers in market m in time period $q(m)$.

Then

$$S_j^q(\theta|W) = \sum_m S_j^m(\theta|W)\pi_q(m) \tag{2}$$

gives the vehicle j's market share for the state of California in quarter q.

5 Data

The California New Car Dealers Association (CNCDA) provides new car registration data for the top 80 car models (accounting for approximately 70% of total sales) every quarter in their Auto Outlook newsletter. This aggregate CA car share data is available for most quarters between 2007 to 2013. In total we have 1674 vehicle-quarter share observations, and an average of 76 vehicles per quarter.[11]

Household-level purchase data is available for PEVs via the California Air Resources Board Clean Vehicle Rebate Project (CVRP). The CVRP dataset includes all PEVs submitted for a CA clean vehicle rebate between March 2010 to the present; according to the Center for Sustainable Energy (2013*b*) (CSE), which manages the project, from March 2010 to 2013 76% of eligible PEVs were submitted for rebates. Additional eligibility criteria require the vehicle to be a new purchase / lease and for the lease to last at least 3 years. Of these transactions 85% participated in the rebate program.[12] Each record in the dataset includes the zip code of the purchaser, the vehicle make, which typically yields the vehicle model, and the date of the rebate application. The latter is used to approximate the quarter of purchase. A representative from the CSE reported between 50 and 60% of participants apply within five days of purchasing the vehicle while nearly 90% apply within 50 days. The mean delay between purchase and rebate application is approximately 25 days.

For each vehicle we collect price (MSRP of the base model) and various standard characteristics from AutoTrader.com and Edmunds. The characteristics included in the estimation are horsepower-weight, length-width ratio, drive type dummy (2 or 4 wheel base), miles per dollar, driving range, and fuel type (electric vehicle dummy). Several are included as

[11] Newsletters in Q3 of 2010 and 2011 and Q2 of 2012 do not report shares. The CNCDA actually reports new car registrations to date in that year. Therefore, quarterly new registrations are backed out by differencing the sales for a particular model between two reports. When one quarter is missing data, the data of the subsequent quarter are also unusable for our estimation.

[12] Other concerns might include varying participation rates by geography or vehicle type. While participation varies from 55% to nearly 100%, it does not appear correlated with the region's income or general political affiliation. A more robust statistic is, unfortunately, not possible with the report's data. Additionally, PHEV rebate participation is slightly lower but generally similar to fully electric vehicle participation.

standards in the literature, others to emphasize characteristics that typically differentiate electric vehicles from gasoline models.

The numerous incentive programs for electric vehicles described in section 2 require adjustments to the baseline specifications for these vehicles. In particular, we consider electric vehicles characteristics taking into account 1) the federal and state rebate, 2) the cost of installing a charging station for their home, and 3) miles per dollar using home charging prices at the cheapest price under their energy provider.[13] We get these rates from the dominant energy provider in the county.

Charging station data is collected from the Alternative Fuels Data Center (AFDC), which in turn collects from major charging station operators Blink, SemaCharge, and Chargepoint, and Open Charge Map (OCM). These data sets provide longitude and latitude coordinates thus allowing great flexibility in how we spatially aggregate the data for use in the model. Data on charging station opening dates are provided in older snapshots (before 2014) of the datasets. More recent snapshots do not include opening dates and deduced by assuming stations that appear between snapshots opened in that period.[14]

We use the Federal Election Commission (FEC) and American Community Survey (ACS) of the US Census Bureau to estimate parameters on political orientation and aggregated income distributions. The ACS is the Census Bureau's recent replacement of the decennial long-form survey, now featuring a continuous survey of up to 250,000 households every month covering a wide range of subjects. Among the available statistics is an annual income distribution estimates across 10 income brackets for most counties in California. Smaller counties are covered by estimates generated from 3 or 5 years of estimates. FEC data provide information on all political contributions over $250. Records are also sufficiently detailed to match most contributions with a recipient political party. We discuss the procedure for generating the estimate of the joint distribution $f_m(y, d, c)$ from the ACS and FEC in Appendix A.

We also utilize demographic data specific to the subset of households that purchase automobiles and electric vehicles with the 2010 to 2012 California Department of Transportation

[13]It might be unreasonable to assume the consumer always charges at the cheapest rate at home, but this method also accounts for the possibility that a lot of charging is actually free from work chargers. We assume consumers install Level 2 chargers at home based on the Center for Sustainable Energy (2013*a*) survey of CVRP benefactors that found approximately 90% of respondents own a Level 2 home charger for their PEV.

[14]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.

CA Household Travel Survey (CHTS) and demographic survey data collected by the CVRP.[15] The former is updated every 10 years and collects demographic information. In total the 2012 to 2013 survey included 42,431 households.[16] 5,717 of the participant households were additionally given GPS devices to track detailed movement information. We use both sets of data to construct highly aggregated statistics on the income of new vehicle purchasers as well as to understand travel behavior to determine relevant charging stations for individuals in certain areas. The latter point is discussed further in Appendix B. CVRP survey participants also report their incomes and thus is used to aggregate statistics on the income of electric vehicle purchasers.

6 Estimation

6.1 Reducing the Parameter Space

To simplify the estimation we reduce our parameter space by a standard technique in the literature. Recall from Equation 1, $\delta_j(\theta) = X_j\beta + \xi_j$, the product-specific term common to all consumers. Because the mean parameters β are linear in δ, we can back out estimates for them after the nonlinear search over δ. Therefore, we refine $\theta = (\beta_e, \beta_d, \beta_c, \sigma', \sigma_e, \sigma_c, \alpha)'$, now with only $K + 6$ parameters. Searching over the J components of δ is expensive, however, so we utilize the share inversion technique introduced by Berry (1994) to "concentrate out" these parameters. This technique requires the restriction that CA-level vehicle shares should match the predicted shares generated by the model at the true parameter values. That is

$$S_j^{DATA} - S_j^{CA}(\delta, \theta_0) = 0 \quad \forall j \tag{3}$$

Given our distributional assumption on consumer tastes, Berry (1994) demonstrates that for each θ, there is a unique $\delta(\theta)$ such that Equation 3 holds. This technique proves useful not only as a mechanism to reduce the parameter space but also to mitigate the endogeneity problem with price by conditioning on the component of the error with which it is correlated, i.e. ξ_j. Given this restriction three more sets of moments identify the parameters θ.

[15] See Table 17 in Appendix C for survey size details.

[16] Despite the name of the survey, households were surveyed from 2012 to early 2013.

6.2 BLP Moments

The first set of moments are the standard demand moments from Berry, Levinsohn and Pakes (1995) using the data set $V = \{V_j\}_{j=1}^J$, the collection of car characteristics W_j and corresponding CA state shares S_j^{DATA} for the J vehicle shares observed. For the benefit of imposing any restriction on the joint distribution of price and ξ_j, these moments require the relatively strong assumption that the demand shock $\xi_j(\theta)$ is mean independent of the observed product characteristics X_j for j in the same markets $(m(j))$ at the true parameter values, i.e.

$$E[\xi_j(\theta_0)|(X_j)_{j\in m(j)}] = 0 \tag{4}$$

Under condition 4 the equation for δ is a standard linear regression model, and $\xi_j(\theta)$ can be backed out as the error from $\delta_j(\theta) - X_j\hat{\beta}_{OLS}$. We are also still exploring an alternative set of moments proposed by Petrin and Seo (2014) allowing for X to be endogenous.

We follow BLP in generating three types of instruments for our first set of moment conditions. For each product the corresponding instruments are

$$Z_j = (X_j, \sum_{j'\in J_f\setminus j} X_{j'}, \sum_{j'\in J\setminus J_f} X_{j'})'$$

where J_f are the set of products offered by firm (make) in the particular market. Hence the instruments are the observable characteristics of the vehicle, the sum of characteristics across the firm except product j, and the sum of characteristics across competitors' product. These instruments proxy for supply-side variables that factor into firm and industry-wide costs correlated with prices but uncorrelated with demand shocks. Theoretically, Z_j is a vector of length $3K$ by 1.[17] These first set of moments can be combined into a $3K$ by 1 vector

$$E[\psi_1(\theta_0, V_j)] \equiv E[\xi_j(\theta_0)Z_j] = 0 \tag{5}$$

with corresponding sample moment at arbitrary θ, $\frac{1}{J}\sum_{j=1}^J \psi_1(\theta, V_j)$.

6.3 Maximum Likelihood Moments

The second set of moments are the score of a maximum simulated likelihood estimator of θ using the CVRP micro purchase data $M = \{M_i\}_{i=1}^N$. Unlike the aggregated data, estimators

[17] In practice we test for strong collinearity among the instruments and drop those that fail this test.

using this sample can take advantage of much greater variation in charging stations and purchasing observations across zip codes and quarters.

Because we observe the time of purchase, model of purchase, and location of individuals in this data set, it is straightforward to write down a likelihood function. For consumer i in market m let I_i be a vector of length $J_{q(m)}$ by 1 of purchase indicators (1 for the vehicle the consumer purchased and specially denoted $I_{ij(i)}$). Conditional on all relevant characteristics of person i, i.e. $D_i = (y_i, d_i, c_i, \{\nu_i\})$, the log probability of observing I_i under parameter θ is given by

$$\frac{1}{N}\sum_{i=1}^{N} L(\theta; M_i) = \frac{1}{N}\sum_{i=1}^{N} I_{ij(i)} \log(P_\theta(j(i)|W, D_i))$$

Following the argument of Goolsbee and Petrin (2004) we claim that conditioning purchase probability calculations on the value of $\delta(\theta)$ described previously eliminates the specification error that might arise because of the endogeneity of price.

However, the available data M_i for the individual does not include income, political affiliation, or idiosyncratic tastes so the probability of purchase must be simulated for each individual by integrating over the distribution $P_m(y, d)P(v)$.[18]

After replacing the purchase probability for a consumer with characteristics M_i with the simulated probability $\hat{P}_\theta(\cdot|W, M_i)$, the sample log likelihood function is

$$\frac{1}{N}\sum_{i=1}^{N} \hat{L}(\theta; M_i) = \frac{1}{N}\sum_{i=1}^{N} I_{ij(i)} \log\left(\hat{P}_\theta(j(i)|W, M_i)\right)$$

The score of the log likelihood function generates $K + 6$ moment conditions

$$E[\psi_2(\theta_0, M_i)] \equiv E\left[\frac{\partial L(\theta_0; M_i)}{\partial \theta_0}\right] = 0 \tag{6}$$

with corresponding sample moment at arbitrary θ, $\frac{1}{N}\sum_{i=1}^{N} \psi_2(\theta, M_i)$.

6.4 Matching Income Distribution Moments

The last set of moments takes advantage of aggregated demographic statistics derived from survey participants in the CHTS and a survey of CVRP participants, data sets denoted by $A = \{A_r\}_{r=1}^{R}$ and $B = \{B_l\}_{l=1}^{L}$, respectively. Following the insight of Imbens and Lancaster

[18]Note c is not simulated. Since we observe the time of purchase and the zip code of the purchaser, we can assign the effective number of charging stations to the individual.

(1994) these aggregated statistics are simply aggregations of micro data; hence aggregate model predictions should match these statistics. Similar to matching moments considered by Petrin (2002) we consider three conditions matching observed income distributions of various categories of car purchasers against model predictions.

The first condition matches 13 income category densities conditional on purchasing a particular make of electric vehicle. Using the data from the CVRP survey and invoking Bayes' rule, i.e. $P(A|B) = P(A,B)/P(B)$, the sample statistics derived are

$$\hat{P}(income_i \in [q_k, q_{k+1}]|i \text{ purchases EV from firm } f) = \frac{\sum_{l=1}^{L} \mathbb{1}(l \text{ purchases EV from firm } f) * \mathbb{1}(income_i \in [q_k, q_{k+1}])}{\sum_{l=1}^{L} \mathbb{1}(l \text{ purchases EV from firm } f)}$$

for $k \in \{1, \ldots, 13\}$ and for f, the six firms that produce electric vehicles in the sample time period, for a total of 78 statistics. q_k for $k \geq 2$ are income cutoffs specified in the CVRP survey data. We assume that the samples are unbiased so the sampling error is 0 in expectation.[19] We will denote the population version of this probability distribution by $\mu = E[\hat{P}(income_i \in [q_k, q_{k+1}]|i \text{ purchases EV from firm } f)]$, where the expectation is taken over sampling error.

The corresponding statistics generated by aggregated model predictions are derived by the following equation.

$$\hat{P}_\theta(income_i \in [q_k, q_{k+1}]|i \text{ purchases EV from firm } f) = \frac{\sum_{m=1}^{M} \sum_{i=1}^{ns} \left[\mathbb{1}(income_i \in [q_k, q_{k+1}]) * \sum_{j \in \{J_q(m) \cap J_f \cap EV\}} \hat{P}_\theta(j|W, D_i)\right]}{\sum_{m=1}^{M} \sum_{i=1}^{ns} \sum_{j \in \{J_q(m) \cap J_f \cap EV\}} \hat{P}_\theta(j|W, D_i)}$$

where $\hat{P}_\theta(j|W, D_i)$ is simulated by integrating over the distribution $P_m(y, d, c)P(v)$.[20] The summation is only over markets covered by the CVRP survey, and EV is used here to denote the set of electric vehicles.

The moment restriction imposes that at the true parameter the model's aggregated statis-

[19] This assumption only requires 1) the CVRP participants taking the survey are not a biased sample of the pool of all CVRP participants and 2) the CHTS sample of households is also not a biased sample of auto purchasers in California.

[20] Note unlike the MLE simulation, here we must also simulate the location of an individual within a market and hence the effective number of charging stations.

tic and the population statistic should be equal.

$$
\begin{aligned}
&E[\psi_3(\theta_0, B_l)] \equiv \\
&\quad \mu(income_i \in [q_k, q_{k+1}] | i \text{ purchases EV from firm } f) \\
&\qquad\qquad - P_{\theta_0}(income_i \in [q_k, q_{k+1}] | i \text{ purchases EV from firm } f) = 0
\end{aligned}
$$

The sample equivalent evaluated at arbitrary θ is $\frac{1}{L}\sum_l \psi_3(\theta, B_l)$ and reflects that all sampling error is driven by the sample distribution used in place of the population distribution μ. Similarly, we construct 20 more moments by matching 10 income category densities conditional on purchasing any vehicle and on purchasing any electric vehicle based on CHTS survey data. The CHTS-based moments are denoted by $\psi_4(\theta, A_r)$.

6.5 GMM Estimator

These four sets of moments can be stacked into a single vector. Formally, we assume that θ_0 uniquely satisfies the population moment conditions described above.

$$
E\left[\psi(\theta_0, U)\right] = E\begin{bmatrix} \psi_1(\theta_0, V) \\ \psi_2(\theta_0, M) \\ \psi_3(\theta_0, B) \\ \psi_4(\theta_0, A) \end{bmatrix} = 0 \tag{7}
$$

with sample analog $\hat{\psi}(\theta, U)$, where $U = (V, M, A, B)$. The GMM estimator $\hat{\theta}$ solves the following criterion function

$$
\hat{\theta} = \arg\min_{\theta} \hat{\psi}(\theta)' W \hat{\psi}(\theta)
$$

where W is a weighting matrix. In practice we follow the Hansen (1982) two-step method, by first estimating parameters where W is the identity matrix and then with W as the inverse of the asymptotic variance matrix of the moments derived from the first step.

7 Identification

7.1 Identifying Taste Heterogeneity

Our utility model requires identifying $K + 6$ non-linear taste parameters from variations across choice sets, charging stations, and demographics in our four data sets. The standard

argument for identifying heterogeneity in tastes using aggregate data follows from Berry, Levinsohn and Pakes (1995). Changes in market shares as choice sets vary across different markets serve as proxies for substitution patterns that the parameters on consumer tastes must explain. One reason we conduct our analysis on all vehicle types rather than just PEVs is to increase variation in choice sets across markets. Moments matching aggregated statistics conditioned on consumer demographics complement potentially weak identification from the aggregate share data. These moments penalize parameter values that fail to reproduce aggregated statistics.

Identifying parameters on terms related to PEVs rely on our data specific to PEV purchases, in particular our rich micro data set from the CVRP. Because electric vehicles, particularly plug-in hybrid electric vehicles, are similar in performance and range to traditional gas-powered vehicles, differences in shares of these electric vehicles from similar gasoline vehicles must be driven largely by PEV-specific tastes.

We also observe significant variation in purchases of electric vehicles as a category and within that category across counties and time. Across geographic markets consumers differ on three dimensions that can explain the differences in purchasing behavior: charging stations, income, and political affiliation. The latter two vary most across geographic markets rather than time, while charging stations vary significantly even over short periods of time as well as across counties. Fixing the number of charging stations at a snapshot in time can thus help pin down income and political orientation parameters, i.e. (α, β_d).[21]

Significant variation in the number of charging stations across time within markets can pin down parameters relating to charging stations. Because markets are defined by time periods as short as a quarter, we do not worry about general improvements in the perception of electric vehicle usage absorbing most of the change in purchase behavior of PEVs from quarter to quarter. Additionally, given a market, the only county-specific factors that significantly change over this short time period are the number of charging stations.[22]

[21] See again, for example, Table 15.

[22] We are, however, concerned about other trends that might be more sensitive to short periods of time. For example the growing peer effect over time might impact purchase of electric vehicles more than new charging stations. In future iterations of this draft, we intend to use our detailed purchase data to proxy for this more direct network effect. A second concern is that charging stations are always increasing over time; we do not observe many instances of charging stations being shut down. We intend to make our results more robust by considering a more natural definition for charging stations, which considers congestion. Effective charging stations by this definition do not necessarily increase over time hence breaking the potential conflation of time and charging stations.

7.2 Endogeneity

Two sources of endogeneity could potentially affect the estimation procedure. The first is the typical assumption that unobserved product characteristics ξ_j are correlated with price p_j. *A priori* these two variables should be positively correlated and generate a positive bias in price elasticity (price elasticity is less negative). Because electric vehicles still tend to carry a higher price than similar gasoline equivalents, the model with bias price would predict consumers are less hesitant to buy high-price electric vehicles than at the true parameter. Ultimately, the bias can force down the magnitude of PEV-specific utility terms to explain the low shares of electric vehicles. As detailed in section 6 we address this issue with the standard tactic in this literature by directly specifying the component of the error with which price is correlated (ξ_j) in our calculation of demand.

A more serious issue for analysis is the potential that charging stations are also endogenous. While we expect demand to increase the number of charging stations, it is also reasonable to suspect the number of charging stations in an area are driven by local demand. The assumption that the unobserved characteristics ξ_j is uniform across counties can amplify the endogeneity. If a county has strong preference towards PEVs, charging stations may be deployed more in the county. However, uniform unobserved demand shock ξ_j may not capture the county-specific preference, leading to an omitted variable problem. The correlation between omitted county specific preference and charging station may result in upward bias of the coefficient.

We deal with this problem in three ways. First, government programs determined the location of 43% of charging stations opened in our sample time period. In conversations with representatives involved in these projects, we learned that the government targeted large areas, such as Los Angeles or San Diego, for receipt of charging stations but specific locations were determined independent of demand. The projects placed charging stations wherever willing partners could be found. Second, we find that charging stations at the household's home zip code are a worse predictor of demand than charging stations in associated "work" zip codes (as determined by travel information in the CHTS).[23] Hence PEV demand is very sensitive to the specific location of these stations. The potential endogeneity problem can then be mitigated by 1) blunt placement of charging stations and 2) considering consumers at the high level of granularity we do.

Finally, charging stations might trend with market-level shocks favoring electric vehicles. Since ξ_j for PEV vehicles is precisely this shock, specifying this component in the calculation

[23] See Appendix B for details.

of demand mitigates the endogeneity problem.[24] Beside these arguemnts, we also tested the robustness of our estimates in subsection 8.1, providing some evidence that they do not suffer from charging station endogeneity.

8 Result

In this section we present the results from our estimation and implications for substitution patterns. *We warn that these results are highly preliminary and have not been subject to standard robustness checks, such as multiple starting values for the optimization procedure. Because precision estimates are subject to change significantly when we complete the second stage of the Hansen two-step GMM procedure, standard errors are not reported here.* Table 4 reports the point estimates for our model of consumer demand.

Table 4: **Demand and Indirect Network Effect Results**

		Mean MU[a]		Std MU[b]
Indirect Network Effect	β_c	0.9455	σ_c	1.0897
PEV	β_e	1.1291	σ_e	1.1476
PEV	β_d	-1.1547		
by Political Preference				
Constant	β_1	1.1837	σ_1	1.0271
Horsepower/Weight	β_2	1.1361	σ_2	1.0776
Length*Width	β_3	1.0179	σ_3	1.078
Drive Type	β_4	1.1414	σ_4	1.0487
MP$	β_5	1.0089	σ_5	1.0952
Range	β_6	0.6899	σ_6	0.1749
Price Sensitivity	α	20.0601		

[a] Mean marginal utility
[b] Standard deviation of marginal utility

The positive PEV parameter, β_e, indicates that the average consumer might have a propensity for electric vehicles over gasoline, but the negative sign on PEV tastes interacted with political preference reveals that on average households with conservative political preference prefer gasoline vehicles. The mean network coefficient β_c is positive, as expected. That is, an expansion in the charging station network has a positive impact on the marginal utility from purchasing a PEV. The implied elasticity of PEV demand with respect to charging stations is shown in the far right column of Table 5. In 2010, the first year when more

[24] Of course, if the number of charging stations is actually highly correlated with shocks specific to a tight array, specifying ξ_j will not completely eliminate the endogeneity problem. In this case, we would need a more sophisticated model of how charging stations are placed. A future iteration on this paper may revisit that question.

Table 5: **Demand and Indirect Network Effect Results**

Year	Sum Share Gas	Sum Share PEV	Avg Elas Gas	Avg Elas PEV	Avg NW[a]
2007	0.000308		-8.99		
2008	0.000235		-8.74		
2009	0.000160		-9.33		
2010	0.000165	0.000003	-9.42	-37.01	0.7295
2011	0.000191	0.000074	-9.22	-22.26	1.6660
2012	0.000219	0.000041	-9.20	-11.31	4.8002
2013	0.000311	0.000059	-8.57	-10.66	6.9867

Sum of shares is average sum of quarterly shares.
[a] Network effect is measured by elasticity with respect to charging stations.

than a 1000 consumers purchased PEVs, our estimates imply a 1% increase in charging units would have led to a 0.75% increase in PEV market share. From 2010 and 2013, this elasticity increased several times each year, suggesting that the network effect is concave with respect to the size of network. Mechanically we see this result because the number of charging stations developed by zip code outpaced the growth in related demand, but the pattern is also intuitive.

One explanation for this pattern is that the early movers of the "early movers" (in the simulation, individuals with a high ε shock) have sufficiently high idiosyncratic demand to push them into PEV purchase. In the context of other common indirect network settings, there are people that purchased Blu-ray players when only a few compatible existed. An alternative is these early movers are truly insensitive to the secondary market (in the simulation, individuals with no weight on the charging station utility term). The former story is supported by examining the implied PEV elasticities from Table 5 (column 4). We find demand for PEVs was less price elastic in 2011 and 2012, possibly explained by early adopters with high idiosyncratic tests for PEVs.

8.1 Robustness Test

In subsection 7.2, we elaborated on the potential endogeneity problem with charging stations: the general preference for PEVs in a given county may have induced more charging station installations, and the uniform unobserved preference ξ across all counties cannot capture the county-specific preference. If there were county-specific unobserved demand shocks and correlated to charging stations, the coefficient on charging station may be biased upward. We test for the prsence of charging station endogeneity. Table 6 shows the regression of county-quarter level charging stations on other county specific demand variables and a proxy for county specific unobserved preference (share difference). Share difference refers to the dif-

ference of county level predicted share and the real share of PEVs[25]. If the share difference is positive for some counties, it implies that the county has higher preference towards PEVs than the state average. If charging station is highly correlated with share difference, our estimate suffers from endogeneity. However, the regression results rejects potential endogeneity. The first column does not include share difference while the second column includes it. The R-squared has barely changed when share difference is added. Moreover, share difference is not significant in explaining the variance in charging stations, implying that unobserved county specific PEV preference is not correlated with charging stations. On the other hand, other county-specific preference variables, such as income and political preference, do affect the charging stations, as expected.

Table 6: **Robustness Test for Charging Station Endogeneity**

	Chg. Stn.	Chg. Stn.
Share Difference[a]		80982.69
		402000
Intercept	474.19	471.39
	313.55	314.15
Income	0.0024	0.0024
	0.001	0.001
Democrats	-977.44	-977.64
	399.98	400.348
Republicans	-1315.30	-1315.63
	352.50	352.828
Quarter	20.37	20.58
	3.58	3.733
N	522	522
R-squared	0.21	0.21
Adjusted R-squared	0.20	0.20

County and quarter level regression

[a] Difference of county level predicted PEV share and real PEV share. It is a proxy for county specific unobserved preference for PEVs.

9 Policy Experiments

Given the preliminary estimates from the demand estimation, we can then predict alternative PEV adoption patterns under two major scenarios: 1) remove the charging stations developed under the EV Project and ChargePoint America, and 2) eliminate tax credit programs.

[25] We do have county level share for PEVs but not for gas vehicles.

Table 7: **Median Percentage Change in PEV Share under Policy Experiment**

Year	No Chg[a]	No Credits[b]	All Chg[c]	All Credits[d]
2010	0.00000	0.00000	3.87218	9.91177
2011	-0.00040	-0.00030	12.80145	17.62225
2012	-0.00099	-0.00007	2.93188	5.95668
2013	-0.00778	-0.00124	7.52128	7.53826

[a] Neither EV Project nor Charge America
[b] No Federal tax credits
[c] Neither EV Project nor Charge America but more credits
[d] No Federal tax credits but more EV Project or Charge America

The first experiment removes charging stations installed by the EV Project and ChargePoint America. Although we know which partners installed the stations for these two projects and that 43% of installations were under these projects, we cannot identify which specific charging stations were placed under these programs. Therefore, we simply reduce charging stations in all EV Project and ChargePoint America counties to 53% of their totals in all periods.[26] Table 7 reports the impact on aggregate shares by year under this alternative scenario in column 3. Without these infrastructure projects, the average PEV share falls most in 2013 (though only by .7%), while the impact is smaller in earlier periods. Again this pattern reflects the insensitivity of early adopters to the secondary market discussed in the previous section. When there is no rebate, the market share of PEV would have decreased by 1.78% thus far. By consumers substituting from gas to PEV vehicles through these programs, carbon emissions have thus far been reduced by 1,650 tons per year. It is equivalent to carbon emissions from 185,664 gallons of gasoline consumed or to the annual greenhouse gas emissions from 347 passenger vehicles.

Given the estimates, we simulated the demand for automobiles under no-rebates or no-government-funded-charging-network scenarios. Without the government funded charging network, PEV market share would have decreased by 16% and 15,000 tons per year, respectively. It is equivalent to carbon emissions from 185,664 and 1.68 million gallons of gasoline consumed, respectively. It is also equivalent to the annual greenhouse gas emissions from 347 and 3,158 passenger vehicles, respectively.

The second counterfactual experiments alters the levels of government tax credits and rebates. The first drys up federal tax credits, which range from $2,500 to $7,500 depend-

[26] This naive way of handling the reduction may be relevant if these government-financed charging stations made up a disproportionate quantity of total charging stations in any period of our sample.

ing on the vehicle model (recall Table 3). Under this scenario, we do not observe a clean pattern of consumer substitution over time, though generally the impact of the rebate becomes pronounced in later periods but always less significant than the impact from the first experiment. Overall, the PEV market share would have decreased by 16% without charging network built by the government. Hence we back out that Carbon emissions have been reduced by 15,000 tons per year due to the switch from gas to PEV vehicles via this channel. It is equivalent to carbon emissions from 1.68 million gallons of gasoline consumed or to the annual greenhouse gas emissions from 3,158 passenger vehicles.

The third and fourth experiments present the artificial government with the choice to fund one but not both projects with the funds originally allocated for both. The third redirects all EV project money into the rebate programs. We simply redirected all $130 million of the EV project and ChargePoint America by removing these stations as described before and adding $2,500 in credits for all PEVs.[27] This intervention makes PEVs almost as cheap as gas vehicles. The fourth counterfactual eliminates federal tax credits but moves the funding to the EV Project and ChargePoint America. Using the estimated total budget of this project in our sample period, we divide the total by the cost of installing a charging station (approximately $1,700 in 2013) and distribute the charging stations across the counties in California. This experiment yields approximately 580 more charging stations in each county by the end of 2013. For example, Los Angeles county had 1,008 charging stations as of the end of 2013. Under this policy experiment, it will have at least one extra charging station every 3 square miles.

The results show that the rebates are slightly more effective than building the charging stations. However, it is surprising that the extra charging stations are worth almost as much as a $2,500 rebate to potential adopters. We can also infer that the larger credits affect early adapters more than charging network but the gap has faded away in the recent years. Another import observation is an economies of scale in the direction of funding. Combining the two projects is far less effective than having one of the projects active. From these results the most effective strategy to expand PEV market would have been to implement rebates program in the early years, then switch to deploying charging network.

[27] This number came from dividing the charging station infrastructure project money and dividing it over all consumers that observed PEV purchasers.

10 Conclusion

The primary goal of this paper is to accurately estimate the magnitude of a secondary market's impact on the growth of a first and to apply that technique to understanding the role incentives and the charging station network have on the growth of plug-in electric vehicle adoption. This draft takes a preliminary step toward that goal by estimating a rich discrete choice model of demand with heterogeneous tastes toward the "network" good in a static setting. Our initial results suggest that the elasticity of demand for PEVs with respect to charging stations is not negligible. In our sample period PEV market share could have increased by as much as 1.6 to 7% (depending on specific PEV model) with a 1% increase in charging stations across California. We also found the role of other incentives was significant, however. We estimate PEV penetration would have been less by .78% without California or federal tax incentives.

We warn, however, that ignoring the feedback mechanism between the primary and secondary markets is a potentially egregious error that may underestimate the importance of early movers in either of these markets to the long-term growth of the market. For a classically durable good like automobiles, shutting down the ability for consumers to forward look with respect to potential growth in the secondary market is an another significant issue that may understate the importance of the network to consumers. We hope to address both of these concerns with the next draft of the paper.

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A Joint Distribution of Income and Political Affiliation

Here we describe the procedure for generating a coarse joint distribution between political preferences and income. 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 when integrating over $f_m(y)$.

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.[28]

B Determination of Charging Station Variable

Understanding which charging stations are relevant to which consumers is a critical part of our analysis and taking advantage of our frequency, high granularity purchase and charging station data. For example, relative to nearby charging stations charging stations in San Francisco are likely insignificant to a consumer in southern Los Angeles. Ultimately we found that work-area charging stations are a superior measure for a consumer's relevant charging stations than charging stations near home. While home 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. According to the Center for Sustainable Energy

[28] We do not use the joint distribution that could be obtained from this survey because of small sample issues. We would be unable to have separate political party distributions by county using the survey.

(2013*a*) survey, approximately 90% of PEV owners own Level 2 home chargers.

Using the California Department of Transportation CA Household Travel Survey (CHTS), which tracked detailed travel information of participants via GPS, we determined destination zip codes for each participant's home zip code (see Table 17 in Appendix C for more survey information). Survey participants document specific trips into four categories: to home, to work, to school, to other. The second panel of Table 18 provides details on trips to school and to work. Work trips are typically longer (over 10 minutes with a stay of over 60 minutes) than school trips; only 1/3 of school trips qualify as "long trips" under this definition, while 2/3 of work trips do. Under the assumption that charging events are more desirable after lengthy battery-draining drives and feasible only during lengthy stays at the trip destination, we focused on work zip codes as the relevant destination zip codes. For each home zip code, there are 11.89 associated work place zip codes on average. 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.

Table 8: **Charging Stations at Work Matters More for PEV Purchase**

	PEV[a]	PEV
Chg Stn at Work	0.1534	0.1459
	0.002	0.002
Chg Stn at Home		0.0162
		0.001
Year	0.2445	0.2449
	0.008	0.008
Constant	-491.601	-492.511
	16.936	16.919
N	57456	57456
R^2	0.204	0.206

Observation level is (home zip code, month) pair.
Sample Period: March 2010 - February 2014
[a] PEV: number of PEV purchase at home zip code

To test whether work zip code charging stations are more relevant to consumers than home zip code charging stations, we use a simple heuristic comparing PEV uptake with charging stations at home versus charging stations at work at the time of purchase. Work zip code charging stations for a particular home zip code are the average of charging stations across all work zip codes weighted by the number of households in that home-work zip code

pair. Table 8 show the results of the regression. It reveals that charging stations in work zip code is more closely related to PEV purchase decision than those in home zip code. It is reasonable result because most PEV purchasers install home charging outlet, which reduce the use of public charging stations around the neighborhood. Figures 4 and 5 in Appendix C illustrate the same closer relationship between demand and work zip code charging stations, rather than home zip code charging stations.

While a course metric for determining whether charging stations matter in influencing purchasing behavior — that is the job of the more complete estimation model — the results do not contradict the theoretical claim that public home charging stations are less significant to PEV purchasers than work charging stations. Actual PEV owner charging behavior, featuring away-from-home charging events, as discussed in section 2 coupled with the common presence of in-home charging units also support that public charging stations are more relevant in work zip codes. Based on this evidence, in our estimation individuals in a certain home zip code are "assigned" the work place charging stations constructed above.

C Figures

Table 9: **Sponsored Charging Infrastructure Projects**

	EV Project	ChargePoint America
Project Period	January 2011 - December 2013	May 2011 - June 2013
Area Covered in CA	Los Angeles, San Diego San Francisco	Los Angeles Sacramento, San Francisco
Funding Institute	Department of Energy (DOE) American Recovery and Reinvestment Act (ARRA)	DOE ARRA
Partnered Charging Network	Blink	ChargePoint
Funding Amount	$130 million dollar[a]	$18.4 million dollar
Total Charging Units Installed[b]	3182	1916
Public Charging Units Installed	933	857

Sources: Project Electric Vehicle Charging Infrastructure Summary Report (Q4 2013), ChargePoint America Vehicle Charging Infrastructure Summary Report

[a] Total budget was $230 million and half of it was funded by the DOE. $130 was allocated to install public or privet charging stations. The rest is operational cost and subsidy for residential chargers.

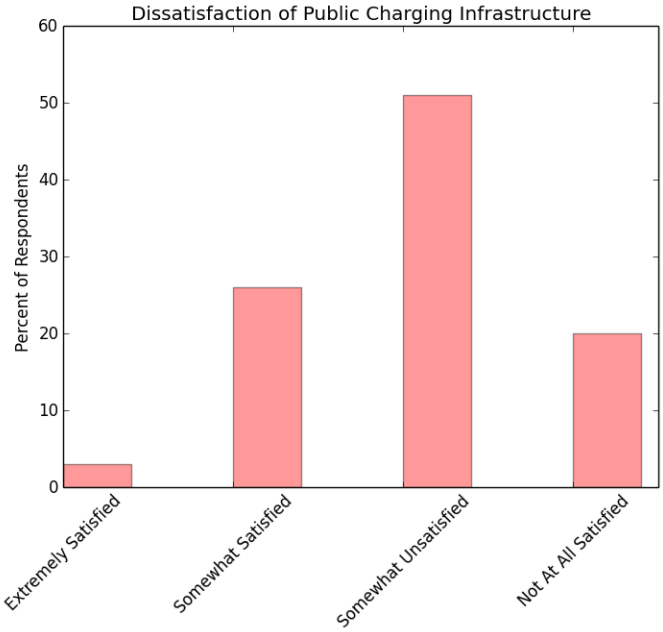
[b] Charging units are counted only in California. Q4 2013

Table 10: **Desired Range Vs. Actual Range**

	Leaf	Volt	Prius
Desired Electric Range	200	100	50
Actual Electric Range	78	38	12
Dissatisfaction with Public Charging Infrastructure	71%		

Source: California Plug-in Electric Vehicle Driver Survey Results, February 2014

Figure 2: **Dissatisfaction with Charging Infrastructure**



Source: California Plug-in Electric Vehicle Driver Survey Results, February 2014

Table 11: **Cumulative Charging Stations in California**

	Public			Private		
	LV1	LV2	DC Fast	LV1	LV2	DC Fast
Q1 2010	0	0	0	0	0	0
Q1 2011	241	81	22	13	109	5
Q1 2012	332	1001	25	25	314	6
Q2 2012	427	1605	31	45	366	6
Q3 2012	453	1761	33	45	379	6
Q4 2012	470	1909	44	45	395	6
Q1 2013	543	2355	63	46	398	6
Q2 2013	584	2694	132	46	410	6
Q3 2013	606	2917	148	46	419	6
Q4 2013	621	3078	180	46	431	9
Total		4665			608	

Source: StationGeo
There are also 153 charging stations of which the ownership is unknown.

Table 12: **Utility Discount for PEV Charging at Home**

Avg Monthly Cost by PEV	Pacific Gas & Electric	Southern California Edison	San Diego Gas & Electric	Sacramento Municipal Utility District
With Discount rate[a]	$31.91	$29.7	$52.8	$26
Without Discount rate[b]	$56.19	$58.09	$62.41	$60.59
Equivalent Avg Monthly Gas Cost[c]			$128.60	

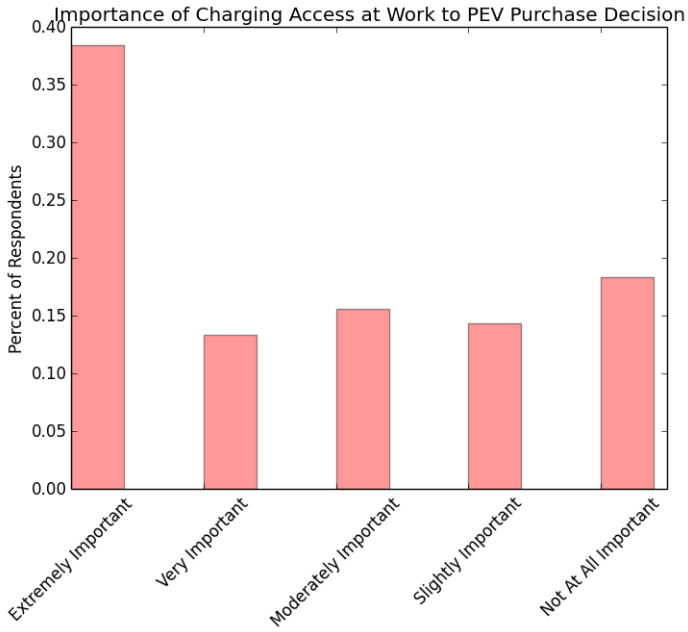
[a] Assuming a LEAF charged during super off-peak time (12:00 AM to 6:00 AM) or off-peak times (11:00 PM to 7:00 AM) under a plan exempt from a tiered rate and is driven 38 miles a day (= 11.02 kwh a day, 330 kwh a month)
[b] Assuming that the current rate plan enjoys no Time of Use rate and charging PEV is in cost tier 101-130%.
[c] At average 2013 gas prices in California

Table 13: **Charging and Driving Behavior**

	LA		SD		SF		CA[b]
	Leaf	Volt	Leaf	Volt	Leaf	Volt	Gas Only
Avg Trip Distance[a]	6.4	7.7	6.6	8.2	7.3	9.39	8.4
Avg Distance per Day	24.8	38	26.7	39.6	27.4	41.4	38.48
Avg Number of Trips b/w Charging Events	3.8	3.8	3.7	3.7	3.5	3	
Avg Distance b/w Charging Events	24.2	28.9	24.6	30.1	25.7	28.1	
Avg Charging Events per Day	1	1.3	1.1	1.3	1.1	1.5	
% Charging Events Away from Home	30	23	23	21	28	21	

Source: EV Project Nissan Leaf Summary Report, Q4 2013, EV Project Chevrolet Volt Summary Report, Q4 2013
[a] Distance is measured in miles.
[b] 2010-2012 California Household Travel Survey

Figure 3: **Charging Access at Work is Important**



Source: California Plug-in Electric Vehicle Driver Survey

Figure 4: **Cumulative PEV Purchase and Charging Stations, Zip 95014**

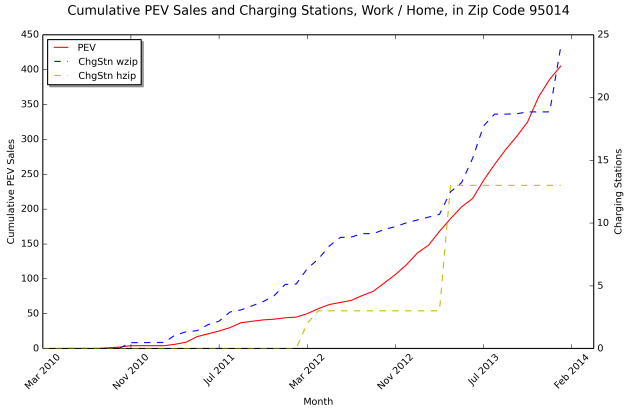


Figure 5: **Monthly PEV Purchase and Charging Stations, Zip 95014**

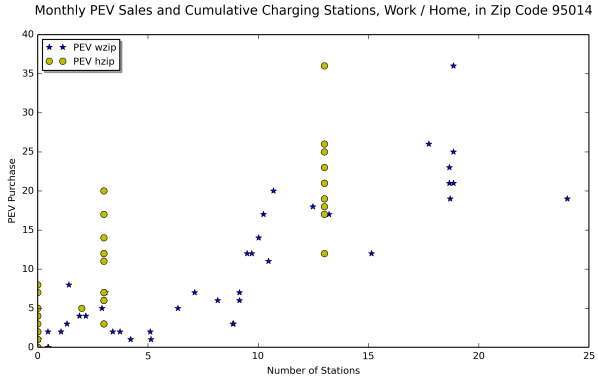


Table 14: **Income Distribution Conditional on a Vehicle or PEV Purchase**

Income 2010-2012	Vehicle Purchase	PEV Purchase
Less than $74,999	0.19	0.07
$75,000 to $99,999	0.16	0.10
$100,000 to $149,999	0.27	0.24
$150,000 to $199,999	0.20	0.23
$200,000 to $249,999	0.09	0.15
More than $250,000	0.10	0.22
Number of Obs	278	92

California Department of Transportation CA Household Travel Survey

Income 2012-2014	LEAF Purchase	Tesla Purchase
Less than $49999	0.03	0.01
$50,000 to $74,999	0.07	0.02
$75,000 to $99,999	0.14	0.03
$100,000 to $124,999	0.15	0.05
$125,000 to $149,999	0.14	0.06
$150,000 to $174,999	0.12	0.07
$175,000 to $199,999	0.10	0.06
$200,000 to $249,999	0.12	0.13
$250,000 to $299,999	0.05	0.10
$300,000 to $349,999	0.03	0.08
$350,000 to $399,999	0.02	0.05
$400,000 to $449,999	0.01	0.05
More than $450,000	0.02	0.31
Number of Obs	1411	1126

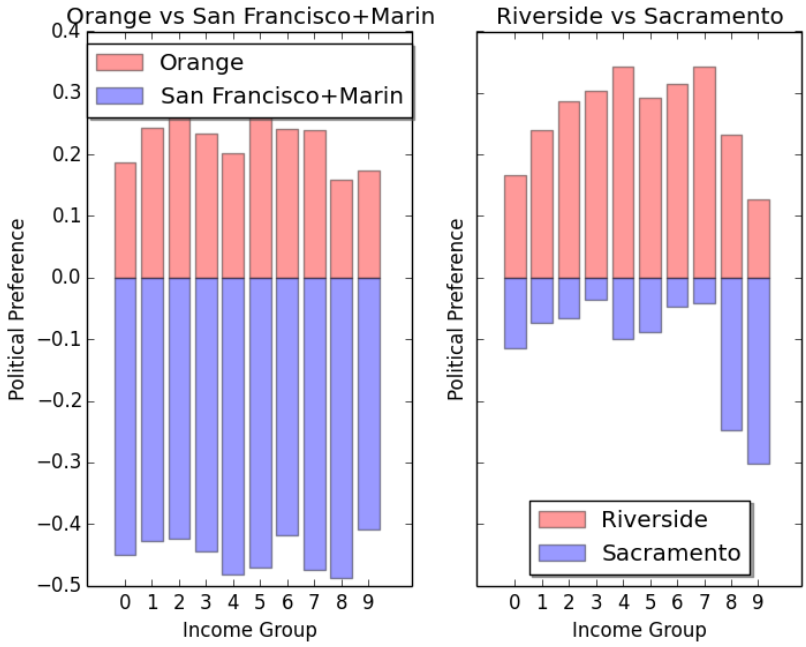
Clean Vehicle Rebate Project EV Owner Demographics and Diffusion Survey

Table 15: **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 PEV sold per 1,000 capita until August 2014, Clean Vehicle Rebate Project rebate data set
[c] Leaf/Volt: ratio between Leaf and Volt demand

Figure 6: **Heterogeneous Income and Political Distribution by County**



Source: Federal Elections Commission
Political preference: -1 if democrats, 1 if republicans, 0 if independent
Income group: percentile of FEC donation given county

Table 16: **CHTS Trips Summary**

	GPS Sample[a]
Sample Period	2010-2012
Number of Households	5,717
Total Number of Trips	285,340
Number of Households	5,717
Number of Home Zip	1,519
Number of Work Zip	859
Total Trips	285,340

Trips	to Work	to School
Total Trips	29,567	30,106
Long Trips[b]	20,491	12,406
Avg Trip Duration[c]	23	16
Median Trip Duration	15	10
Min Trip Duration	1	1
Max Trip Duration	679	1080
Sd Trip Duration	23	24
Avg Stay Duration	225	223
Median Stay Duration	376	132
Min Stay Duration	1	1
Max Stay Duration	1,409	1,349
Sd Stay Duration	225	231

2010-2012 California Household Travel Survey
[a] GPS samples are subset of the total samples who recorded their trips as well.
[b] Trips which required more than 10 minutes of drive and more than 60 minutes of stay
[c] Duration is measured in minutes

Table 17: **CHTS and CVRP Survey Summary**

	CHTS[a]	CVRP[b]
Survey Period	2010 - 2012	Oct 2013 - May 2014
Vehicle Purchase Period	1994 - 2012	Sept 2012 - Apr 2014
Number of Respondents	42,431	8,415
Sample Used	1588	6,602
Car Purchase	278	6,602
PEV Purchase	92	6,602

[a] California Department of Transportation CA Household Travel Survey. CVRP surveyed only PEV purchasers who applied for CVRP rebate.
[b] Clean Vehicle Rebate Project EV Owner Demographics and Diffusion Survey.
In the micro income moments we only used the samples which has the income and purchase year are known.

Table 18: **Statistics of Work and Home Zip Code Pairs**

	Work Zip	Home Zip
Avg Number of Corresponding Zip Codes[a]	20.74	12.24
Med Number of Corresponding Zip Codes	10	11
Sd Number of Corresponding Zip Codes	34.30	9.10
Avg Num of Hhlds Commuting/Living	36.97	21.83
Med % of Hhlds Commuting/Living	14	17
Sd Number of Hhlds	91.83	20.46
Number Work-Home Pair	17791	
Avg Number of Hhlds for Work-Home Pair	1.78	
Med Number of Hhlds for Work-Home Pair	1	
Sd Number of Hhlds for Work-Home Pair	2.52	

California Department of Transportation CA Household Travel Survey.

[a] Corresponding zip codes of work zip codes refer to the number of associated home zip codes. If at least one household described that they commute between the two zip codes, the zip code pair is considered as "associated".