FACTORS AFFECTING PLUG-IN ELECTRIC VEHICLE SALES IN CALIFORNIA

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CALIFORNIA AIR RESOURCES BOARD
RESEARCH DIVISION
CALIFORNIA ENVIRONMENTAL PROTECTION AGENCY
1001 I STREET
SACRAMENTO, CALIFORNIA 95814

PREPARED BY:

UNIVERSITY OF CALIFORNIA, LOS ANGELES
LOS ANGELES, CA 90095

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Abstract

This report provides an overview of the growth of California’s plug-in electric vehicle market from 2010 to 2015, describing several trends in the adoption of plug-in electric vehicles (PEV). It also identifies the household, housing, geographic, market and public policy factors that are correlated with the sales of new PEVs. The research finds that electric vehicle sales are not evenly spread across neighborhoods. During our study period, neighborhoods ranked in the top 25% by socio-economic status had purchased over 10 times more PEVs than neighborhoods in the bottom 25%. In addition to household income, the presence of single family homes has a very large and positive correlation with PEV sales.

The research also found that policies designed to incentivize PEV purchases are positively and significantly associated with higher PEVs sales. The state program that permits drivers of single-occupancy PEVs to access carpool lanes was shown to have a particularly strong positive association with increased PEVs sales in communities near carpool lanes. The Clean Vehicle Rebate Project that offers incentives for the purchase of eligible plug-in electric vehicles was also found to have a positive and significant correlation with additional sales. This research also shows that offering tiered and progressively higher rebates to moderate- and lower-income households increases policy cost effectiveness and equity outcomes. Recent policy modifications—to the Clean Vehicle Rebate Project, the Enhanced Fleet Modernization Program (EFMP) and EFMP Plus-up Pilot Program—were consistent with our findings and suggest that these updated policies are now both more cost effective and more equitable.

Chapter 1: Executive Summary

Plug-in electric vehicles (PEV) advance California's goals for reducing greenhouse gas emissions. Several state policies seek to increase the adoption of PEVs and other types of zero emission vehicles (ZEV). For example, the Zero Emission Vehicle regulation is designed to increase the automakers' supply of ZEVs. The Clean Vehicle Rebate Project provides rebates to California residents for the purchase of new, eligible PEVs. The Enhanced Fleet Modernization (EFMP) Program and EFMP Plus-up Pilot Program help low-income individuals and families retire old polluting vehicles and purchase cleaner and more fuel-efficient cars.

This report provides an overview of the growth of California's plug-in electric vehicle market from 2010 to 2015, describing several trends in the adoption of PEVs. With these trends as context, this report's central objective is to identify the household, geographic, market and public policy factors that appear to influence the sales of new PEVs. While most of our analysis will focus on PEVs as a vehicle class, in some instances we will differentiate PEVs into two subsets: battery electric vehicles (BEV) from plug-in hybrid electric vehicles (PHEV).

To conduct the study we obtained data on the number and types of PEVs that California residents registered by month and by census tract, and then integrated this information with data on households, neighborhoods, commuting patterns, market and policy conditions across the state. We then conducted various kinds of statistical analyses to evaluate the magnitude, direction and accuracy of the measured correlations between vehicle sales and the aforementioned conditions. Though not funded as part of this study, we also conducted a survey of California new car buyers to learn more about household preferences for specific types of plug-in electric vehicles.

1.1 Summary of Findings

Our analysis using data provided by HIS Inc. revealed that 125,000 PEVs had been sold in California by the start of 2015. This represents an average annual growth rate of 77% per year.

Neighborhood Dynamics
We found that this growth in vehicle sales is not evenly spread across neighborhoods. Through October of 2014, neighborhoods ranked in the top 25% by socio-economic status had purchased over 10 times more PEVs than neighborhoods in the bottom 25%, a divergence that appears to be widening over time. Neighborhoods that adopted PEVs early continued to purchase PEVs at a higher rate than neighborhoods that adopted them later.

Households
Our survey found that spatially concentrated growth in PEVs is associated with household and housing characteristics. Households' income, housing value, and the presence of single family

homes have a very large and positive correlation with PEV sales. Other household characteristics that are positively correlated with PEV sales include household fleet sizes, the ability to charge at home, and commuting distance. In the reverse, a neighborhood's proportion of multi-family homes exhibited a negative correlation with PEV sales.

The survey also revealed a highly segmented market of new car buyers, with some segments more willing to purchase plug-in electric vehicles than other segments. The market segment most willing to purchase PEVs (which represents approximately 31% of new car buyers) revealed no diminishment in the utility they derived from plug-in hybrid electric vehicles (PHEVs) but modest diminishment in the utility they derive from battery electric vehicles (BEVs) compared to conventional vehicles. This suggests incentives especially for the purchase of BEVs were an important contributor to sales.

Regional Variations

PEV patterns are also expressed regionally. The Los Angeles region (Los Angeles and Orange Counties) leads the state in total PEVs purchased, followed by the San Francisco Bay Area counties and then San Diego County. There are also distinct trends in vehicle type across metropolitan areas. For instance, residents of the San Francisco Bay Area counties have exhibited a higher propensity to purchase BEVs relative to PHEVs while the Los Angeles region has exhibited the opposite propensity. The San Francisco Bay Area counties also exhibited relatively robust sales growth, relative to other regions, even as gasoline price declined in 2015.

Vehicle Characteristics

Over 28 different light-duty PEV models were introduced over the study period. The cumulative sale of battery electric vehicles and plug-in hybrid electric vehicles were roughly equal through the study period. With respect to vehicle body type, compact cars have led in annual and cumulative sales over the period of study, but mid-sized and subcompact plug-in electric vehicles only emerged with significant market share in 2012 and 2013 respectively.

Refueling Needs and Fuels

Our new car buyer survey also revealed household preferences for longer battery ranges, higher electric fuel efficiency and access to residential and workplace charging. An analysis of changes in gasoline prices revealed that a decrease in gasoline prices (such as occurred in 2015) was correlated with a reduction in PEV sales.

Public Policies

We found that policies designed to induce and support PEV purchases are positively and significantly associated with higher PEVs sales. The state program that permits drivers of single-occupancy PEVs to access High Occupancy Vehicle lanes (HOV, also referred to as carpool lanes) was shown to have a particularly strong positive association with increased PEVs sales in communities near HOV lanes. The Clean Vehicle Rebate Project that offered incentives for the purchase of eligible plug-in electric vehicles was also shown to have a positive and significant correlation with additional sales. This research also showed that offering tiered and progressively higher rebates to moderate- and lower-income households increases policy cost effectiveness and equity outcomes. The Clean Vehicle Rebate Project and the Enhanced Fleet Modernization Program & EFMP Plus-up Pilot Program have recently been modified to include progressively-tiered rebates thereby enhancing their cost effectiveness and equity impacts.

Caveats and Limitation

This research attempted to evaluate the correlation between plug-in electric vehicle sales and i) the spatial prevalence of publicly-accessible charging stations and ii) the market timing of new model introductions. However, data limitations prevent a valid and precise evaluation of these correlations. Finally, the aforementioned findings arise from the very early plug-in electric market in California and will change as household attitudes, residential charging opportunities, vehicle and fuel markets and public policies continue to evolve.

1.2 Introduction

The modern plug-in electric vehicle (PEV) market began in December, 2010. The state of California has enacted a suite of policies to support growth in this market. These policies include the Zero Emission Vehicle (ZEV) regulation designed to increase the automakers' supply of PEVs and other ZEVs. The Clean Vehicle Rebate Project (CVRP) provides rebates for the purchase of new ZEVs while the Enhanced Fleet Modernization Program (EFMP) and the EFMP Plus-up Pilot Program provides even higher rebates to help low-income individuals and families retire old polluting vehicles and purchase cleaner and more fuel-efficient cars. In addition, a state decal program permits single-occupancy ZEVs to drive in high-occupancy lanes. Finally, a range of state and local programs have sought to subsidize the cost of installing charge stations and to increase access to charge stations by having investor owned utilities install and own them at ratepayer cost. The ostensible objective driving many of these policies has been the Governor's goal of having 1.5 million zero-emission vehicles (ZEV) on California roads by 2025.

Surprisingly little research exists on the growth of California's PEV market and the effect that these policies have had on it. As we embarked on this market analysis we found no pre-existing state-wide analyses of PEV market trends or other California-focused studies of factors or policies associated with PEV market growth. Even the availability of data has been fairly limited, with most observers relying on the data provided by the Clean Vehicle Rebate Project. However, very uneven uptake of these rebates by consumers has meant that this data, though expertly presented, is not representative of the broader market. (For example, while over 80% of eligible Tesla buyers apply for rebates only 57% of Ford owners do so.)[1]

1.3 Report Road Map and Research Questions

This report begins to fill this gap in our understanding of the spatial and temporal development of the PEV market and more importantly, the determinants of its growth. Chapter 2 presents an overview of the data and methods that we employ in subsequent chapters.

Chapters 3, 4 and 5 identify and evaluate non-policy factors that may influence PEVs sales. More specifically, Chapter 4 then uses multivariate analysis to identify and analyze the strength of household, neighborhood and other such factors in predicting the sale of these vehicles. Chapter 5 assesses the determinants of vehicle rebate uptake as well as the influence of new model introductions on PEV sales.

Chapters 6, 7 and 8 evaluate the effects of various policies on PEV sales, and in some cases distinguish between effects on BEV versus PHEV sales. Chapter 6 explores how the spatial

[1] A misconception that BEV purchases have exceeded PHEV purchases appears to have emerged from misinterpretation of CVRP data. Based on actual sales data, roughly equal proportions of BEVs (51% or 87,735) and PHEVs (49% or 84,887) were registered between December 2010 and October 2015. However, using available CVRP data, the comparable figures for BEVs are 59% (73,066) and PHEVs 41% (51,729) because BEV buyers are almost 20% more likely to apply for rebates than PHEV buyers.

proximity of HOV lanes has influenced PEV sales across neighborhoods. Chapter 7 provides insight into how differences in households' willingness to pay for BEVs and PHEVs may interact with rebate levels to influence sales in the future. Finally, Chapter 8 evaluates how alternative designs of rebate levels offered to purchasers of BEVs and PHEVs would likely affect vehicle sales. Chapter 9 concludes by reflecting on what we have learned and where important gaps still remain in our understanding of this market and supporting policies.

The following sections further explain the research questions addressed in these chapters.

Understanding Market Trends and Neighborhood Influences

What kinds of PEVs, how many and how fast? In Chapter 3 we first identify broad sales trends across the state, regions and types of neighborhoods. Our motivating questions focus on how the rate of PEV sales has differed along different dimensions during the first four years of the market. Has state-wide and regional growth been evenly paced or erratic? Are there shifts or slow-downs that policymakers should notice?

We also explore how sales trends differed across types of PEVs. Specifically, what are trends in the shares of BEVs and PHEVs sold? Observers have speculated on whether differences in vehicle characteristics, levels of customer acceptance and rebate levels have affected vehicle sales. These broad trends between BEVs and PHEVs are explored in much greater detail using neighborhood characteristics in Chapter 4 and household preferences in Chapter 7. We also want to know how sales of differing PEV body types have trended. This analysis sheds light on what types of vehicles are available to consumers and how well they have gained consumer acceptance.

A first cut: How do neighborhoods and regions differ? We next identify broad trends across different types of neighborhoods. We describe how the propensity to purchase PEVs differs across neighborhoods with different socio-economic profiles. (This more descriptive analysis sets the stage for a deeper identification of specific socio-economic mechanisms in Chapter 4.) We also focus on how the timing of neighborhood entry into the PEV market affects subsequent sales. Does the fact that some neighborhoods begin to purchase PEVs early and others much later in time affect the future and cumulative sales rates in these neighborhoods? This analysis is also bolstered later in Chapter 4 when we examine how much of a neighborhood's PEV growth can be explained by its socioeconomic, cultural and transportation characteristics versus how much exposure (how long) neighborhoods have been purchasing PEVs.

Neighborhood differences may reflect important regional differences in sales growth across the state. Thus we examine broad trends across major regions within California, identifying regions with significantly different rates of growth. We also map PEV, BEV and PHEV growth within major metropolitan areas. This reveals whether sales are spatially concentrated or diffused.

A deeper dive: What neighborhood characteristics predict PEV adoption? In Chapter 4 we dig beneath the broader trends to better understand what neighborhood characteristics are most correlated with, or best predict, PEV sales. While a simple mapping of PEV sales suggests high spatial concentration, little evidence has been produced on the role that specific neighborhood characteristics play in PEV sales. The first half of Chapter 4 presents evidence on how important specific factors have been in explaining differences in PEVs sales across neighborhoods. Integrated into these analyses is the timing of neighborhood adoption of PEVs. This enables us to explore the effect of past exposure to PEVs in comparison to socio-economic and related neighborhood characteristics. We also differentiate among PEVs, by identifying those neighborhood characteristics that may explain why some neighborhoods appear to purchase more BEVs than PHEVs. Lastly, we ask what neighborhood characteristics best predict purchasing trends of used PEVs.

Understanding the Influence of PEV Policies on Behavior and PEV Sales

Which neighborhoods take advantage of PEV rebates? During the study period, certain consumers who purchased PEVs were eligible to receive a clean vehicle rebate of $1,500 for PHEVs and $2,500 for BEVs in California.[2] Our analysis suggests that not everyone who was eligible actually applied for the rebate. Low uptake rates may signal a lack of policy awareness on the part of both the dealership and buyers, which if remedied, may lead to higher PEV sales. In the first half of Chapter 5 we explore what explains differences in neighborhoods' vehicle rebate uptake. Have rebate uptake rates changed over the time? Do uptake rates appear to vary across types of PEVs purchased? Chapter 8 addresses whether, and by how much, rebates might increase PEV sales.

Has the introduction of new PEV models significantly increased aggregate PEVs sales? One of the goals of California's ZEV regulation is to increase the production of PEVs with the hope that providing a greater choice of PEVs will lead to greater PEV sales. In the second part of chapter 5, we evaluate how the introduction of PEV models over time has affected PEVs sales. More specifically, we explore the role that brand loyalty has played by evaluating the effect of introducing PEV versions of pre-existing models, such as the Ford Fusion or Toyota Prius. We also evaluate how the introduction of sequential models into a body-type class affects PEV sales.

[2] Except for a few months in the early part of the market, the CVRP did not have an income cap during our study period. Since March 29, 2016, however, higher income consumers are no longer eligible for CVRP rebates if their gross annual income exceeds $250,000 for single tax filers, $340,000 for head of household filers and $500,000 for joint filers. For low- and moderate-income consumers, CVRP rebates for all types of eligible light-duty passenger vehicles increased by $1,500. The income eligibility changes applied to rebate applications for vehicles purchased or leased on or after the implementation date of March 29, 2016.
Sources: 1) California Clean Vehicle Rebate Project Income Eligibility: https://cleanvehiclerebate.org/eng/income-eligibility 2) Center for Sustainable Energy: "CVRP Initiates New Eligibility Requirements March 29, 2016" https://energycenter.org/article/cvrp-initiates-new-eligibility-requirements-march-29-2016

Does having access to high occupancy vehicle (HOV) lanes increase a neighborhood's purchases of PEVs? In California, owners of PEVs can apply for a sticker that gives them, as a single-occupancy vehicle, access to California's network of HOV lanes until 2019. The policy goal of providing these drivers access to less congested HOV lanes is to increase PEV sales. In Chapter 6, we evaluate whether neighborhoods with access to more HOV lane miles are more likely to purchase PEVs than neighborhoods with no access to HOVs lanes. HOV lanes miles are distributed unevenly across the major metropolitan areas since they are created in the more congested segments of the freeway network. In light of this, we also explore whether expanding HOV lane access (by distributing more stickers) would have different effects across the major metropolitan areas in California.

How do different types of households value BEVs and PHEVs? In Chapter 7 we turn to a deeper exploration of how different types of households value BEVs and PHEVs. Our analysis in Chapter 4 of how neighborhood characteristics were correlated with the purchase of BEVs and PHEVs was limited in several ways. Most importantly, this analysis of neighborhoods could not tell us how different types of households would value the incorporation of BEV and PHEV technologies in vehicles they are likely to purchase over the coming years. To understand California's different consumer segments, we estimate how much each segment is willing to pay for new BEVs and PHEVs. How big are these different consumer segments? Do some segments prefer one type of technology over another? And, given the segments' respective size, how likely is the state to reach its PEV goals? Even more specifically, we need to know how much buyers in each of the consumer segments would be willing to pay for expanded electric range, access to HOV lanes, and greater fuel economy. In this chapter we describe the analysis of our 2013-14 survey of new car buyers in California that allows us to answer these important questions.

Having such highly-resolved consumer preference information can aid in the design of PEV policies in several ways. First, it can assist in more effectively designing rebate levels and targeting those rebates to consumers that would otherwise not have purchased PEVs. If there are differences in consumer willingness to pay for BEV versus PHEVs, this disparity can shed light on how rebates should differ across these vehicles. Second, for federal policies designed to increase battery productivity and lower battery costs, this analysis can help identify preferred battery ranges and characterize consumers' willingness to pay for this increased range in vehicles. Third, our analysis will describe how much consumers value the improved fuel economy of PEVs, thereby shedding light on the importance of programs (such as those of state-regulated Investor Owned Utilities that operate charging stations) deciding how to price electricity used as a transportation fuel. Finally, we estimate how much consumers are willing to pay in the form of higher vehicle prices to access HOV lanes, which complements our analysis of HOV lane proximity in Chapter 6.

How have vehicle rebates affected PEV sales? As already discussed, the State of California offers financial incentives for the purpose of PEVs through the Clean Vehicle Rebate Project. In Chapter 8 we explore the critical question of whether, and how much rebates increase sales of

BEVs and PHEVs. We also evaluate the cost effectiveness of the existing rebate program. This involves understanding how many buyers would *not* have purchased a PEV in the absence of rebates, and conversely, how many consumers who received rebates would have purchased PEVs without them. This enables us to develop a cost effectiveness measure of rebate programs that estimates rebate dollars spent per additional PEV sale induced. State legislation (SB 1275 and SB 535) has sought to improve the equity impacts of rebate programs for consumers of different income levels.

Might there be even more cost effective rebate designs? As of May 2015, new Enhanced Fleet Modernization and Plus-up Pilot Programs[3] provide higher rebate levels to lower-income households in areas that have not attained air quality standards. In addition, policymakers have considered the effectiveness of adding a vehicle price cap which would make higher-priced PEVs ineligible for the state rebates. The second half of Chapter 8 uses the economic analysis done in Chapter 7 to simulate the effects of alternative rebate designs. We evaluate policies recently adopted and proposed in terms of i) the number of additional PEVs purchased, ii) total program cost, iii) cost per additional vehicle purchase induced and iv) the distribution of rebate funding across consumer income classes.

[3] The California Air Resource Board initiated a pilot project in the Greater Los Angeles area and San Joaquin Valley to help low-income individuals and families get rid of old polluting vehicles and purchase much cleaner and more fuel-efficient cars. The program works by providing increasingly larger cash payments for the lowest-income families to move up to the very cleanest cars. Under this program, for example, it is possible for a family that meets the income guidelines to receive $12,000 toward the purchase of an electric car. See http://www.arb.ca.gov/newsrel/efmp_plus_up.pdf.

Chapter 2: Data and Methods

2.1 Introduction

This chapter gives an overview of the data sources and methods employed in this report. We used a variety of methods and in some cases a mix of methods. As a result, we will go into more detail regarding methods in each respective chapter.

2.2 Data Sources

This analysis used two primary and multiple ancillary data sources:

1) **IHS Automotive Vehicle Registration Data**: The most important source of data were monthly records of new and used[4] Plug-in Electric Vehicle (PEV) and Hybrid Electric Vehicle (HEV) registrations by California census tract between December 2010 and October 2015. Chapter 9 (on the correlation of gas prices with PEV sales) used data from 2015, but for the rest of our study, the period analyzed was December 2010 through the end of 2014/start of 2015. The HIS data included information about the make, model and body type of each vehicle, the dealership at which the vehicle was purchased and the vehicle manufacturer suggested retail price (MSRP). For used vehicles, information on vehicle miles travelled (VMT) were also provided. These data create a comprehensive snapshot of temporal and cross-sectional trends in PEV and HEV ownership in California. (Source: IHS Automotive Industry Solutions (2016). *Custom Market Reports and Data Feeds*. Retrieved in 2015 from https://www.ihs.com/products/automotive-market-reports-data-feeds.html)

2) **2008-2012 American Community Surveys (ACS)**: The ACS is a national annual survey run by the US Census Bureau, which collects data on Americans' social, economic, work and demographic characteristics. The Census Bureau releases five-year census-tract level averages for most data collected. We used data from the ACS to better understand what types of census tracts were adopting PEVs over time. A census track contains approximately 4,674 persons during our study period.[5] We used statistics from three broad categories: demographic (age, gender and racial distribution of a tract), economic (income and home value distributions of a tract) and work/commuting (number and type of workers in a tract, length and mode of commute for workers within a tract, vehicle ownership within a tract). A more comprehensive list of variables is included in the Chapter 2-Appendix A. (Source: U.S. Census Bureau. (2008-2012). *2012 American Community Survey 5-Year Estimates*. Retrieved from http://factfinder2.census.gov.)

[4] Used registrations were only available for January-October 2015.
[5] Per the 2009-2013 American Community Survey (U.S. Census).

3) **Caltrans HOV Lane**: We used data from Caltrans on HOV lane locations within California to determine how many miles of HOV lanes existed within a 30-mile radius of the center of each census tract. These calculations were conducted using GIS. (Source: California Department of Transportation (Caltrans) (2015), "California High Occupancy Vehicle Lanes." Retrieved from http://www.dot.ca.gov/hq/tsip/gis/datalibrary/Metadata/HOV.html)

4) **Energy Information Administration (EIA) Gasoline Price Data:** The EIA releases monthly gasoline prices for all US states. For our analysis, we used data on the historical monthly average gasoline price for California between January 2011 and October 2014. (Source: U.S. Department of Energy, Efficiency and Renewable Energy. (n.d.). "Gasoline Prices by Formulation, Grade, Sales Type." Retrieved from http://www.eia.gov/dnav/pet/pet_pri_allmg_a_EPM0_PTC_Dpgal_m.htm)

5) **Center for Sustainable Energy (CSE) PEV Rebate Data:** The CSE maintains a database of all PEV rebate claims in California. We used data on the number of monthly rebate claims by census tract for all months up to October 2015. (Source: Center for Sustainable Energy (2016). California Air Resources Board Clean Vehicle Rebate Project, Rebate Statistics. Data last updated March 14, 2016. Retrieved 2015 from https://cleanvehiclerebate.org/rebate-statistics)

6) **Presence of Charging Stations:** We used data from the U.S. Department of Energy's Alternative Fuels Data Center. We used data as of December 2015 on publicly-available plug-in electric vehicle charger density (Level 1 Chargers, Level 2 Chargers, and DC Fast Chargers within a 5-mile radius of the population centroid of each census tract). (Source: U.S. Department of Energy, Efficiency and Renewable Energy. (n.d.). "Alternative Fuels Data Center." Retrieved from http://www.afdc.energy.gov/data/data/?q=charging)

7) **Political Support for Proposition 23:** We used voting district data regarding California's Proposition 23 as a measure of a district's green propensity. California Proposition 23 was a 2010 ballot measure to suspend AB 32, "Global Warming Solutions Act of 2006." A proportion of "no" votes should correlate to a higher green propensity, and vice versa. (Source: The State of California, California Secretary of State Alex Padilla (n.d.). "General Election – Statement of Vote, November 2, 2010." Retrieved from http://www.sos.ca.gov/elections/prior-elections/statewide-election-results/general-election-november-2-2010/statement-vote/)

8) **Utility Electricity Price Data:** We used pricing data from the California Energy Commission to determine electricity and petroleum fuel cost. (Source: California Energy Commission (2016). Energy Almanac. Retrieved in 2015 http://energyalmanac.ca.gov/electricity/ and Southern California Edison (2016). Retrieved in 2015 sce.com/rates)

9) **UCLA New Car Buyer Survey**: We administered an online survey to a representative sample of Californian new car buyers and obtained a sample of 1,261 completed surveys. Of the respondents who completed an initial screener, approximately 42% both qualified as potential new car buyers meaning that they intended to purchase a new care within the next three years. The completion rate for respondents that started this survey was 98% while the representativeness check on this sample are presented as part of the subsequent analysis.

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

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

GfK's KnowledgePanel is a probability-based panel designed to be statistically representative of the California population. Because all KnowledgePanel households were selected randomly with a known probability of selection, KnowledgePanel estimates can be used with the statistical confidence required.

Initially using random-digit-dialing (RDD), KnowledgePanel is now continuously maintained using the United States Postal Service's Delivery Sequence File. This file is essentially a complete list of all California residential households, including households that are cell phone-only and often missed in RDD sampling. Persons in selected households are then invited to participate in GFK's Web enabled panel. Those who agree to participate, but are not already on the Internet, are sent a laptop computer and receive an Internet service connection provided and paid for by GfK. People who already have computers and Internet service are permitted to participate using their own equipment.

Latino Subsample: The sample for KnowledgePanel Latinos uses a dual frame design. The main sample is recruited through the mail using English and Spanish materials. This address-based sample (ABS) is drawn from the U.S. Postal Service's Computerized Delivery Sequence file that covers approximately 97% of the physical addresses. The ABS mail sample represents all households whether they have only cellular telephone service, a landline telephone or no telephone service. The ABS sample is further supplemented with a smaller RDD telephone recruitment that specifically targets high density Latino areas. This RDD sample is designed to exclusively recruit additional Spanish-dominant households. As a result, KnowledgePanel Latino has the most complete coverage of the California Latino population.

2.3 Data Methods

We employed a wide range of data methods in this report, which are summarized in Table 2-1. The purpose of these methods in chapter 3 is to reveal trends in PEV sales over time. By contrast, the methods in chapter 3 and 4, and 5 are primarily used to describe the correlation between PEV trends and other neighborhood factors that may influence them. In Chapter 7 what changes is that we use methods that can describe how specific types of households (rather than neighborhoods) value specific attributes of PEVs. Chapters 5 and 8 incorporate more sophisticated methods to explore the relationship between changes in policy-influence variables (access to HOV lanes and rebate levels) and PEV sales.

Table 2-1: Chapter Methods

	Primary Methods
Chapter 3	• Longitudinal data analysis • Cross tabulation
Chapter 4	• Least Absolute Shrinkage and Selection Operator (LASSO) • Cross tabulation
Chapter 5	• Ordinary Least Squares (OLS) regression analysis
Chapter 6	• Generalized Propensity Score (GPS) matching approach • Classification and Regression Tree Analysis (CART) • Poisson regression • Generation of dose-response curves • Metro-level simulations
Chapter 7	• Stated preference survey with novel choice and pivot design • Multinomial mixed logit model with willingness to pay estimates • Alternative specific constant (ASC) logit model • Latent class logit model with consumer segment analyses
Chapter 8	• Stated preference survey with novel choice and pivot design • Numeric simulations

2.4 Overview of the More Advanced Methods

Many of the analytical methods used in these chapters are standard statistical methods. However, we also take advantage of some newer advanced methods to tackle particular questions. In this section we give the reader an overview of three of these more advanced methods. Because of the need to undertake specific validity and data quality checks for each of these methods, we do have methods subsections in many of the latter chapters that provide more details.

Absolute Shrinkage and Selection Operator (LASSO) regression.[6] In chapter 4, we created models to predict which census tracts purchase electric vehicles. To create these models, we used a statistical technique called Least Absolute Shrinkage and Selection Operator (LASSO) regression. Typical regression analysis takes a set of variables and assigns a weight to each variable such that prediction error is minimized. That is, if we had a room full of children and we wanted a model to estimate their height based on their age, the process of regression will tell us what to multiply the child's age by to get the prediction for his or her height. However, in the case of predicting electric vehicle sales, we have a large number of potential variables to choose from (225 from the ACS, which is already a subset from a much larger number) and it is not clear what the best predictors of census tract vehicle sales will be. Although it is tempting to just put all predictors into the model, this may not be the best method for two reasons. First, predictive models can be overfit; that is, putting more and more variables into the model can improve our prediction in this specific instance, but will actually make our prediction less likely to be correct if we try to apply it in another setting (i.e. PEV sales next year). Second, in many cases only a few variables explain most of the differences between observations. Thus, adding more variables does not improve prediction very much, but makes the model much more difficult to interpret.

LASSO is a statistical technique that helps us identify which variables have the most power to predict the outcome that we care about. Unlike normal regression, it balances assigning weights to variables to create the best possible prediction against a penalty for adding additional variables. If a variable does not add enough explanatory power, Lasso will restrict its weight to be 0. For instance, in the classroom example, although in a random classroom students with red hair might be slightly taller, LASSO would likely assign this variable a weight of 0 because it explains very little of the overall differences in classroom height. In this way, LASSO regression can provide us with models that use only a small subset of possible variables, but still have very high explanatory power. Even better, LASSO provides ways to test how well the model is expected to perform in other contexts, helping protect against the overfitting problem described above. Using LASSO regression in this report, we are able to create models that predict well which census tracts purchase PEVs while using only a small number of explanatory variables.

Generalized Propensity Score Methods. In Chapter 6 we use a generalized propensity score approach (Hirano and Imbens, 2005) to estimate the impact of HOV lanes on PEV registrations, controlling for the probability of treatment (HOV lane density). Standard propensity scores for matching conditions on a binary variable, e.g., whether or not a census tract is near HOV lanes. However, we are interested in a continuous conditioning variable, namely, how many miles of HOV lanes a census tract is near. First, we estimate a generalized propensity score (GPS) for each census tract, which tells us the probability of treatment, based on a large set of

[6] Varian (2014) discusses how LASSO and other types of penalized regression models commonly used by data scientists can help economists build better predictive models.

demographics. Controlling for propensity score, we estimate a dose- response curve, which tells us how PEV registrations change as the number of nearby HOV lanes increases.

Few papers have employed the generalized propensity score methodology. Chapter 6 represents a novel application of GPS with several innovations. First, we use an unusual treatment variable, miles of HOV lanes within a thirty mile radius of the population centroid of a census tract. Our unit of analysis, the census tract, allows us to explore geographic heterogeneity by aggregating estimated effects at the metropolitan area level. Second, we use a Least Absolute Shrinkage and Selection Operator (LASSO) method to select first stage control variables, resulting in propensity scores that balance observables very well across census tracts with differing levels of treatment.

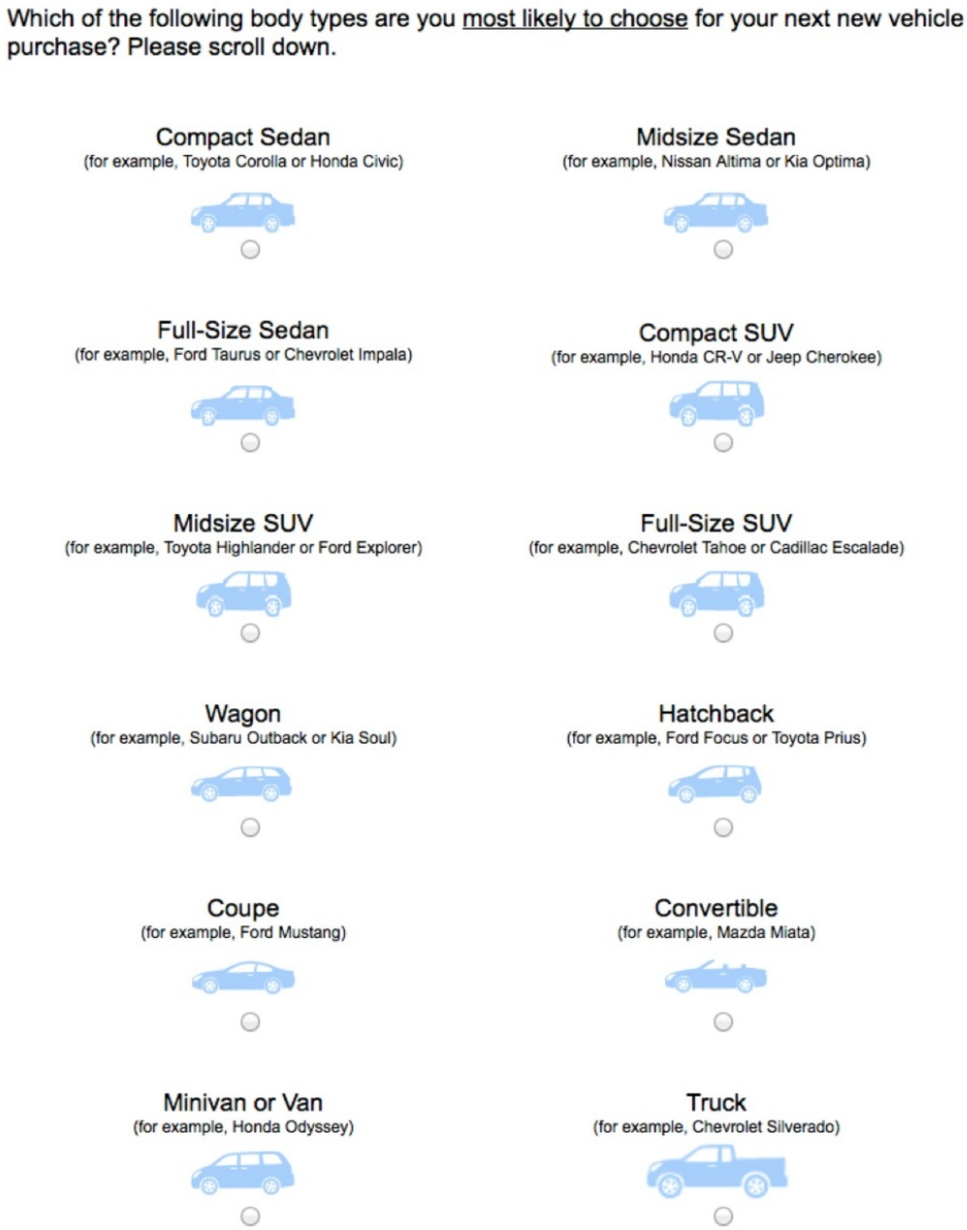
Stated Preference Methods In Chapters 7 and 8 we analyze data from a survey of Californian new car buyers. In 2014 we administered an online survey to a representative sample of Californian new car buyers and obtained a sample of 1,261 completed surveys.[7]

The survey first gathered household, vehicle, and demographic data. Next, the survey elicited body and brand preferences. Respondents were asked to choose the top two vehicle body types (out of twelve options) they were most likely to select for their next new vehicle purchase, as shown in Figure 2-1.

Once we understood households' preferences for the body and brand, we constructed a set of equivalent BEV and PHEV vehicles for these body types and brands. In our stated preference choice experiments, we then mix these BEV and PHEVs models in with equivalent ICE models. In this way our survey approach is forward-looking in that it elicits consumers' preferences for BEV and PHEV types that are not yet available but are likely to be in the coming market. This allows us to present PEV choices that go beyond the two dozen or so models that were available to consumers in order to explore their preferences more thoroughly.

[7] Of the respondents who completed an initial screener, approximately 42% qualified both as potential new car buyers.

Figure 2-1: New Car Buyer Survey: Body Choice



Which of the following body types are you most likely to choose for your next new vehicle purchase? Please scroll down.

Compact Sedan
(for example, Toyota Corolla or Honda Civic)

Midsize Sedan
(for example, Nissan Altima or Kia Optima)

Full-Size Sedan
(for example, Ford Taurus or Chevrolet Impala)

Compact SUV
(for example, Honda CR-V or Jeep Cherokee)

Midsize SUV
(for example, Toyota Highlander or Ford Explorer)

Full-Size SUV
(for example, Chevrolet Tahoe or Cadillac Escalade)

Wagon
(for example, Subaru Outback or Kia Soul)

Hatchback
(for example, Ford Focus or Toyota Prius)

Coupe
(for example, Ford Mustang)

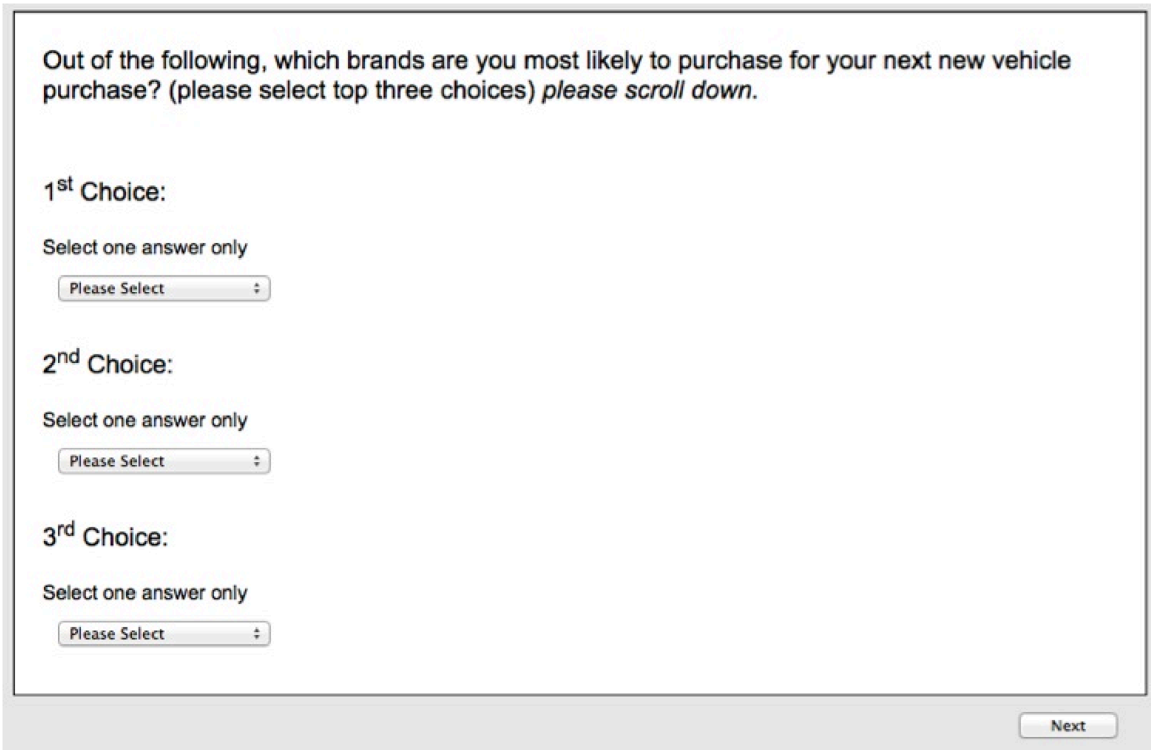
Convertible
(for example, Mazda Miata)

Minivan or Van
(for example, Honda Odyssey)

Truck
(for example, Chevrolet Silverado)

Then respondents were asked to select the top three brands (out of the twenty most popular brands by sales volume in California in 2012) they were most likely to select for their next new vehicle purchase, as shown below in Figure 2-2.

Figure 2-2: New Car Buyer Survey: Brand Choice


Out of the following, which brands are you most likely to purchase for your next new vehicle purchase? (please select top three choices) *please scroll down.*

1st Choice:

Select one answer only

Please Select

2nd Choice:

Select one answer only

Please Select

3rd Choice:

Select one answer only

Please Select

Next

Next, respondents were shown four sets of five vehicles, as displayed in Figure 2-3, and in each set were asked to choose which of the five vehicles they were most likely to select for their next new vehicle purchase. The total set of twenty vehicles respondents chose from included only conventional vehicles (including internal combustion engine vehicles, hybrid electric vehicles, and diesel-fueled vehicles) on the new vehicle market as of the Fall of 2013. It included specifically the vehicles that are of both the top brand and top body selected by respondents. The remainder of the twenty included a random draw of vehicles that are of the top body choice and second or third brand choice, or of the second body choice and top brand choice. In cases where the set of vehicles that meets these criteria is less than twenty, the remainder of the vehicles was a random selection of vehicles that are of either one of the top body selections or of the top brand selections.

Figure 2-3: New Car Buyer Survey: Top Vehicle Choice

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

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

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

Next

Finally, respondents were asked to choose which one of the four vehicles chosen as top picks out of the twenty vehicles in the previous five questions they would be most likely to select for their next new vehicle purchase, as shown below in Figure 2-4. This 'top' vehicle and its characteristics are carried through to subsequent questions in the survey.

Figure 2-4: New Car Buyer Survey: Top Vehicle Choice

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

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

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

Next

Respondents were provided with information on BEV and PHEV technologies and introduced to PEV attributes, including refuel price, electric range, and HOV lane access. Finally, respondents were asked to choose between the conventional version, two BEV versions, and two PHEV versions of the vehicle they previously indicated as their top choice. (This approach presents consumers with a wide set of brand and body types containing BEV and PHEV technologies that are likely to become available.)

In each choice set the first column displayed the conventional vehicle, and we randomized whether the two BEVs or PHEVs appeared in the subsequent columns. Attribute levels vary for each vehicle version as shown in Table 2-2, with the hypothetical price oriented in reference to the price of the existing conventional vehicle. An example choice set is shown in Figure 2-5.

Table 2-2: Attribute Levels

Purchase Price[1] (% of conventional)				
Gasoline	100%			
BEV	105%	115%	125%	150%
PHEV	105%	115%	125%	150%
Gasoline Refuel Cost ($ per gal)				
Gasoline[2]	$4.00	$4.40	$4.80	$5.60
BEV	n/a			
PHEV[3]	$2.00	$2.20	$2.40	$2.80
Electric Refuel Cost[4] ($ per gal equivalent)				
Gasoline	n/a			
BEV	$0.90	$1.10	$1.50	$2.50
PHEV	$0.90	$1.10	$1.50	$2.50
Gasoline Range (miles)				
Gasoline	300			
BEV	0			
PHEV	300			
Electric Range (miles)				
Gasoline	n/a			
BEV	50	75	100	200
PHEV	10	20	40	60
HOV access				
Gasoline	no			
BEV	no, yes			
PHEV	no, yes			

[1]The respondent sees price in dollars. For example, a respondent who selected a conventional model that costs $30,000 would see BEV and PHEV versions of that model that cost $31,500, $34,500, $37,500, or $45,000.
[2]At the time the survey was administered, average gasoline cost in California was approximately $4 per gallon.
[3]The average gasoline fuel economy of PHEVs as of December 2013 was 41mpg, which is roughly double the fuel economy of our gasoline vehicle universe of 20mpg. Therefore we choose a baseline refueling cost for PHEVs that is half that of gasoline vehicles.
[4]At the time the survey was administered, the average overnight electricity rate in California was roughly 16 cents per kilowatt hour (kWh) and the average vehicle economy of electric vehicles was 3.5 miles per kWh, suggesting an average cost per electric mile of $0.046. The average cost per mile of gasoline vehicles in our vehicle universe is ($4/gal)/(20mi/gal) = $0.20 per mile. Thus, on average, refueling cost for electric miles is 23% of the $4 per gallon refueling cost for gasoline miles, or $0.92/gal. Therefore, we choose a baseline electric refueling cost of $0.90 per gallon equivalent.

Figure 2-5: New Car Buyer Survey: PEV vs. Conventional Vehicle Choice Module

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

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

Next

We used NGENE choice experiment software to design the experiment. The efficiency of an experimental design can be greatly improved if we know the approximate magnitude or even the sign of the true parameters (Scarpa and Rose, 2008). For example, by assuming that the coefficient on price is negative, or that consumer utility for an alternative is reduced as that alternative gets more expensive, we no longer need an experimental design that can distinguish between a negative or positive coefficient, but can instead more precisely estimate a negative coefficient.

Specifically, we use an algorithm in NGENE that allows us to maximize the amount of information we are able to extract from our choice experiment by minimizing the variance-covariance estimator of the vector of utility function coefficients. The algorithm searches through potential experimental designs with different combinations and levels of attributes. We select the experimental design with the smallest determinant of the asymptotic variance-covariance matrix, also known as the D-error.[8] To further increase the efficiency of the design,

[8] For more details see Scarpa and Rose (2008).

we specify Bayesian priors. That is, for each coefficient that we seek to estimate, we specify an assumed a priori distribution based on existing market data and prior PEV studies. We base these assumptions on parameter estimates from earlier studies looking at PEV attributes (Bunch et al., 1993; Golob et al., 1993; Brownstone, Bunch, and Train, 2000; Ewing and Sarigöllü, 2000; Hidrue et al., 2011; Qian and Soopramanien, 2011; Achtnicht, Bühler, and Hermeling, 2012).

Chapter 3: Plug-in Electric Vehicles Sales Patterns in California

3.1 Introduction

Since 2010, new plug-in electric vehicle (PEV) purchases have grown rapidly in California, reaching over 175,000 vehicles by 2015. During this time PEVs made up more than 3% of California's annual new vehicle sales. This chapter describes the PEV market's development, characterizing its broad trends. Section 3.2 describes the over two dozen PEV models introduced to the California market through 2014, identifying their year of introduction, total sales volume and rank in terms of total cumulative sales (i.e. which model has sold the most units).

While most of our analysis will focus on PEVs as a vehicle class, in some instances we will differentiate PEVs into two subsets: battery electric vehicles (BEV) from plug-in hybrid electric vehicles (PHEV). Many factors may affect the relative sales of BEVs and PHEVs. First, the limited battery and driving range associated with some BEVs may reduce BEV sales relative to PHEV sales. Conversely, more generous subsidies in the form of state rebates and federal tax credits may increase BEV sales relative to PHEV sales. A last reason for differentiating BEV from PHEV sales is the hypothesis that BEVs may be driven more electric miles and thus yield larger environmental benefits.

In some instances we will also compare PEV sales with hybrid vehicle sales trends. Because PEVs share many features in common with hybrid-electric vehicles (HEV), the latter provides a useful comparison or benchmark. Relative to vehicles with internal combustion engines, both vehicle types emit fewer emissions, operate with greater fuel efficiency and lower maintenance costs, incorporate new technologies and tend to cost more. HEVs, which were first introduced in the early 1990s, also enjoyed similar state-level rebates and federal-level tax credits. Finally, households who initially purchased hybrids because of their green benefits, fuel economy and risk-tolerance for new technologies are likely to value PEVs relatively highly. PEVs, hydrogen fuel cell vehicles and others comprise what California Air Resources Board calls advanced clean vehicles.[9] As an indicator of PEV market acceptance and position, we will compare PEV market penetration to clean vehicles as a broad group.

Section 3.3 presents several broader trends in this market which will help motivate and contextualize the rest of the report. We describe how the rate of sales has varied over time for

[9] See the California Air Resources Board for further details on the classification of vehicles at http://www.arb.ca.gov/msprog/consumer_info/advanced_clean_cars/consumer_acc_mtr.htm

PEVs, BEVs and PHEVs as well as hybrids.[10] Next, we consider trends that begin to identify the deeper determinants and patterns of growth which will be further evaluated in Chapters 4 and 5. We describe how socioeconomic characteristics of neighborhoods correlate with the rates of PEV, BEV, PHEV, and HEV sales. We also explore how early versus late adopting census tracts differ over time in terms of tract PEV purchases. We then explore how the above factors come together to create different rates of PEV growth across regions within California. Lastly, focusing within metropolitan areas we describe the degree of spatial concentration in PEV sales as well as BEV and PHEV sales.

3.2 Vehicle Introductions and Sales Volumes

Table 3-1 shows PEV sales between 2010 and 2014 by release year and model across California.[11] During this time period, almost 120,000 PEVs in over 28 models were sold in California. In recent years, the number of new models released each year has remained fairly constant. Based on automakers announcements, this rate is expected to continue through 2016.

Despite the large number of models illustrated in Table 3-1, most of the volume in this market is concentrated in a few models. The final column of the table provides a top 10 ranking by cumulative sales. Early entrants in 2010 including the Chevrolet Volt (rank 1st), Nissan LEAF (2nd), and the Tesla Model S (4th) lead the market in total sales. PEV versions of pre-established models comprise the remaining types found in the top 10.[12]

[10] Plug-in Electric Vehicle (PEV) is a general term for any car that runs at least partially on battery power and is recharged from the electricity grid. There are two different types of PEVs to choose from – BEV and PHEV. Pure BEVs run completely on electricity stored in batteries and have an electric motor rather than a gasoline engine. PHEVs combine two propulsion modes in one vehicle – an electric motor that is battery powered and can be plugged in and recharged, and a gasoline engine that can be refueled with gasoline. Sources:
http://driveclean.ca.gov/pev/Plug-in_Electric_Vehicles/PEV_Types.php
http://driveclean.ca.gov/pev/Plug-in_Electric_Vehicles/PEV_Types.php#bev
http://driveclean.ca.gov/pev/Plug-in_Electric_Vehicles/PEV_Types.php#phev

[11] California, with over 40 percent of the US market, reveals market trends that characterize other states as well.

[12] These include Toyota Prius (3rd), Ford Fusion (5th), FIAT 500 (6th), Ford C-Max (7th), Toyota RAVA 4 (8th), Smart Car (9th), and Spark (10th).

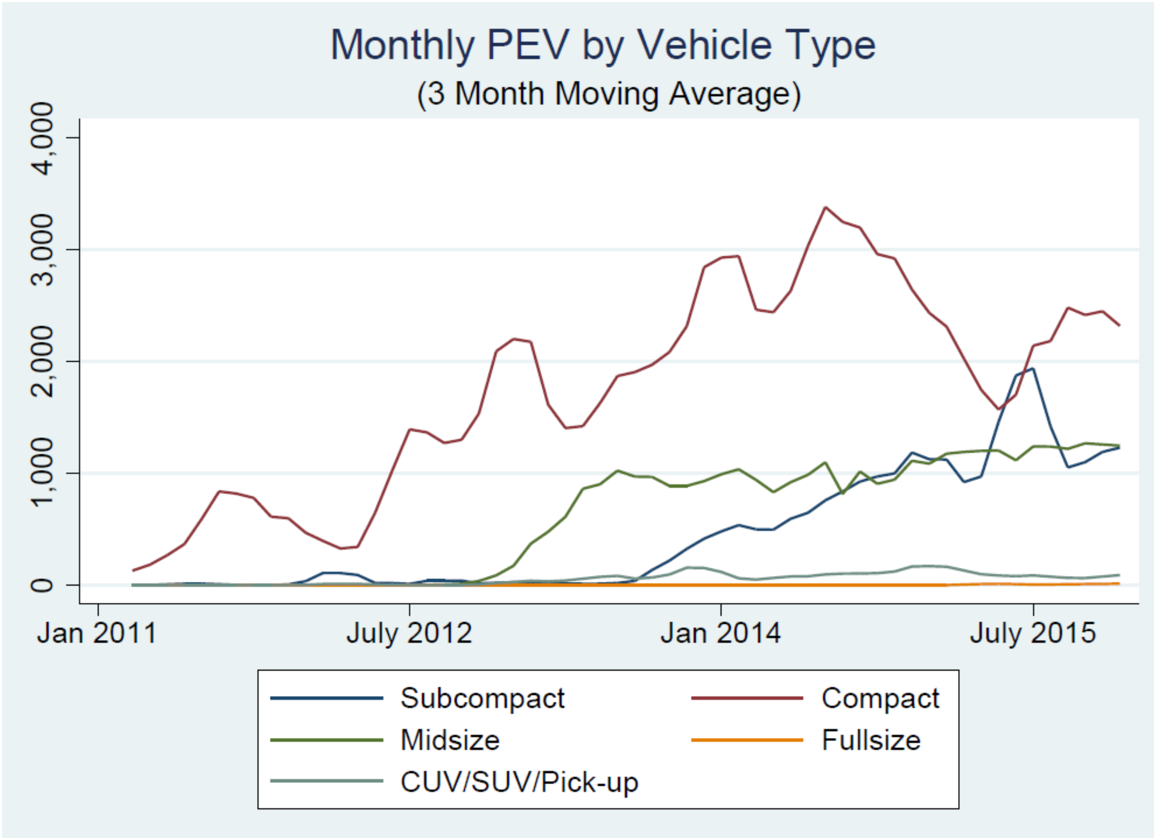
Table 3-1: Sales of PEV Models Released by Year and Body in California, 2010 - 2014

Release Year	Model	Body	Sales*	Top 10 Ranking
2010	TESLA ROADSTER	Luxury Coupe	156	
	NISSAN LEAF	Hatchback	25,206	2
	INTERNATIONAL ESTAR	Van	37	
	CHEVROLET VOLT	Hatchback	26,197	1
2011	SMARTCAR FORTWO	Coupe	2,122	9
	AZURE TRANSIT CONNECT	Van	59	
	MITSUBISHI I-MIEV	Hatchback	255	
2012	BMW ACTIVE E	Luxury Coupe	457	
	FORD FOCUS ELECTRIC	Hatchback	1,209	
	TESLA MODEL S	Luxury Hatchback	15,521	4
	HONDA FIT EV	Hatchback	92	
	TOYOTA RAV4 EV	SUV	2,221	8
	FISKER KARMA	Luxury Sedan	270	
	TOYOTA PRIUS PLUG-IN	Hatchback	18,163	3
2013	CHEVROLET SPARK	Hatchback	1,338	10
	FIAT 500	Hatchback	7,736	6
	FORD C-MAX ENERGI	Hatchback	6,002	7
	HONDA ACCORD PLUG-IN	Sedan	589	
	FORD FUSION ENERGI	Sedan	7,945	5
2014	BMW 13 BEV PLU	Hatchback	896	
	MERCEDES-BENZ B-CLASS BCL	Hatchback	565	
	KIA SOUL EV	SUV	286	
	CADILLAC ELR	Luxury Coupe	302	
	PORSCHE PANAMERA S HYB	Luxury Sedan	202	
	MCLAREN PI PLU	Luxury Coupe	15	
	BMW 13 REX HYB	Hatchback	1,040	
	PORSCHE 918 SPY PLU	Luxury Coupe	14	
	VOLKSWAGEN GOLF SPR PLU	Hatchback	219	

Source: IHS 2010-2014

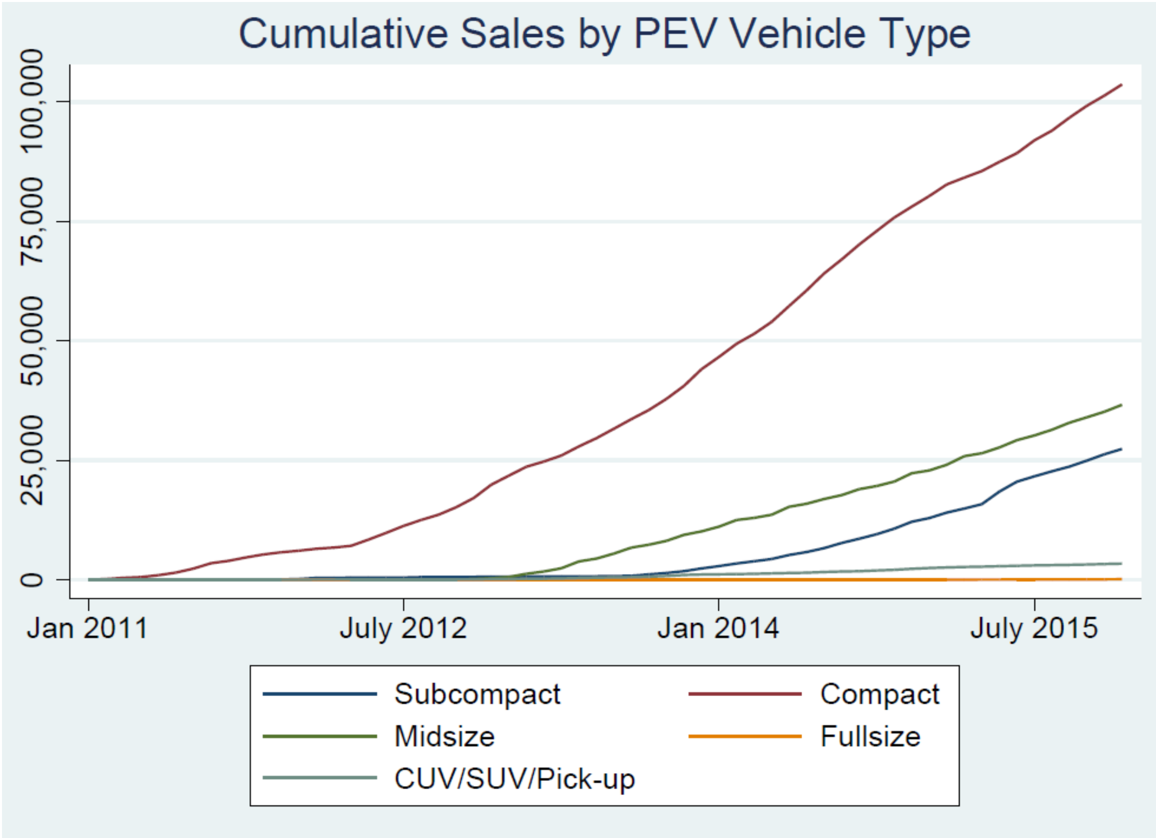
Over half of these models are hatchbacks or smaller coupes, although larger sedans, coupes and SUVs have also been introduced and are beginning to penetrate these product niches. Figure 3-1A reveals that compacts represented the largest share of the PEVs for almost every month between 2010 and 2015, except for being overtaken briefly by subcompacts in 2015. The rise of mid-size body types in late 2012 is a notable market development which has persisted. This is followed by a market rise in subcompacts in 2013, which captured significant and steady market share through 2015. Figure 3-1B shows similar trends, but in terms of cumulative sales over the entire period of study.

Figure 3-1A Trend Share of Body Type by Monthly Sales



Source: IHS 2010-2015

Figure 3-1B Trend Share of Body Type by Cumulative Sales



Source: IHS 2010-2015

3.3 PEV Market Trends

Next we present and explore broad trends in PEVs sales. We organize our analysis around several related questions:

1. How have PEV sales evolved over time? How have the sales of BEVs and PHEVs evolved over time? How have sales of PEVs relative to hybrids evolved over time since their respective introduction?

2. How do these market trends vary by socio-economic characteristics of neighborhoods? How do these trends vary for a neighborhood ranked among the top 25% versus the bottom 25% in terms of income and education?

3. How do these trends vary across census tracts when tracts are grouped, (earliest to latest), by the date of their first PEV purchase? How does PEV sales growth in earlier-adopting neighborhoods compare to later-adopting neighborhoods?

4. How do these market trends vary across California's regions? Which regions have the largest share of the market? Which regions are growing faster than others?

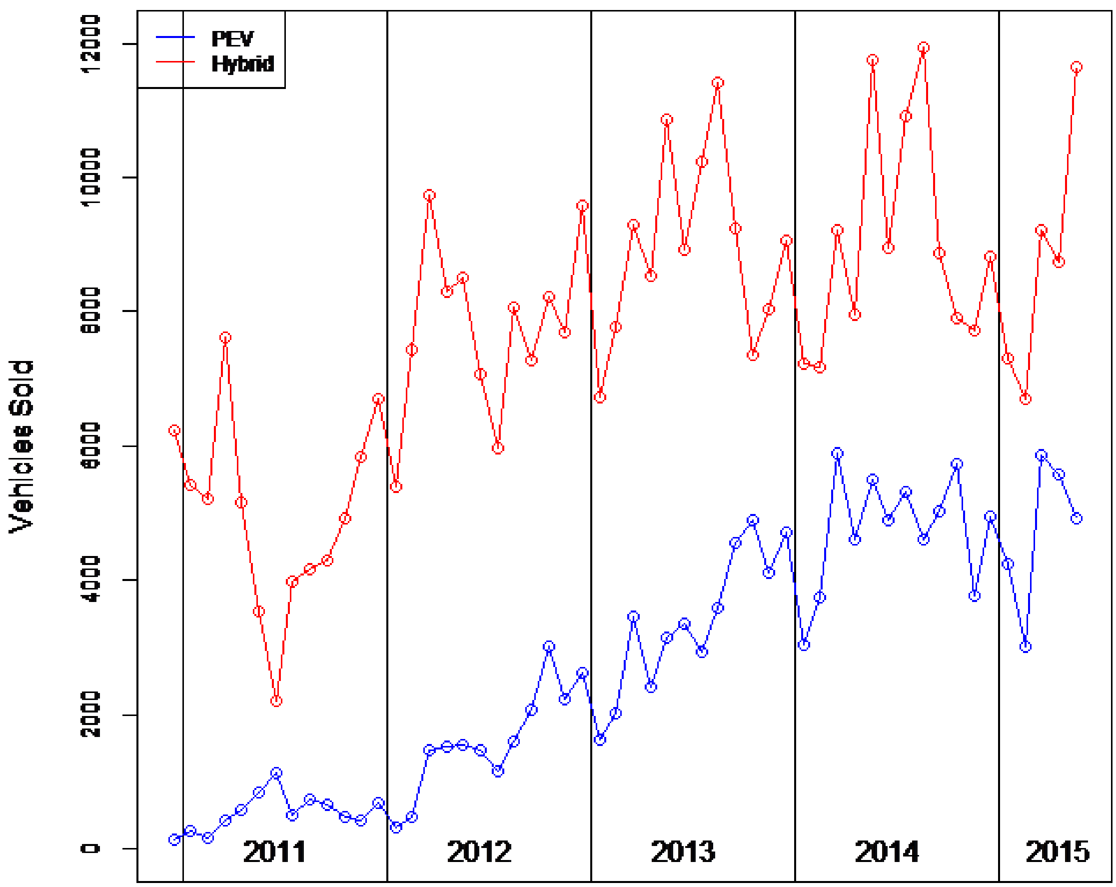
5. How do these market trends vary within regions in California? Do BEV and PHEV sales differ from each other within metropolitan regions?

This descriptive analysis informs much of our subsequent research in this report. For example, observed differences in the propensity to purchase BEVs relative to PHEVs and PEVs relative to hybrids are the focus of analysis in later chapters. Similarly, we will describe which neighborhood characteristics are most correlated with the observed differences in the propensity to purchase BEVs relative to PHEVs and PEVs relative to hybrid vehicles based on analysis presented in this chapter.

Trend 1: Rate of PEV Purchases Peaked during 2014, Flattening Out in 2015

Beginning in 2010, the rate of monthly PEV sales grew rapidly through 2014 as shown in Figure 3-2. Monthly sales increased from 319 PEVs sold in January 2012 to 3,030 sold in January 2014. In 2014 this rate of growth began to slow considerably with 2015 monthly sales stagnating at or below 2014 levels. Figure 3-2 shows that hybrid sales, by comparison, also grew over this same period, though not as fast.

Figure 3-2: Monthly PEV and HEV Sales in California (Dec 2010 – May 2015)

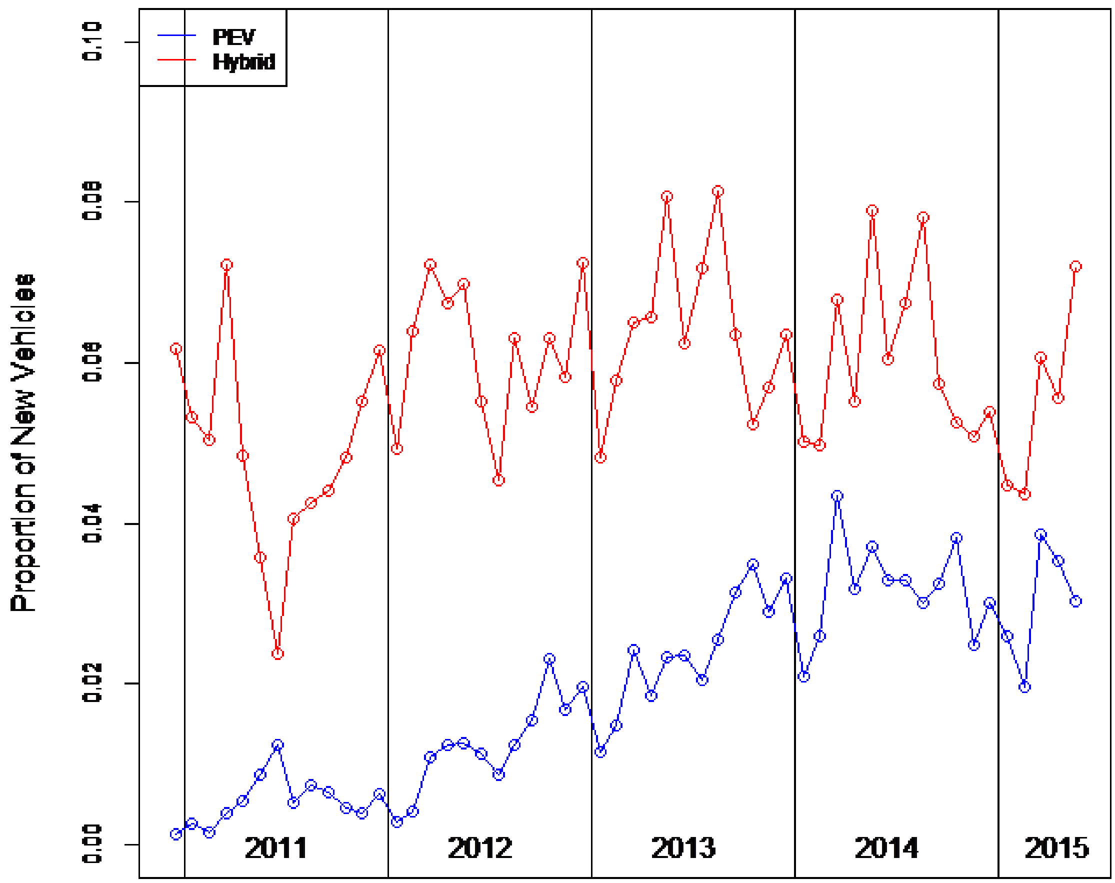


Source: IHS 2010-2015

Trend 2: Gap closes between PEV and HEV Sales as PEVs' Share of clean vehicles Increases

Figure 3-3 shows monthly HEV and PEV sales as a percentage of all new monthly vehicle sales in California. Between the end of 2011 and the end of 2013, PEVs increased from less than 0.5% of all new vehicle sales to more than 3% of all new vehicle sales. However, this rate stays roughly constant for all of 2014 and 2015 (with some seasonal variation).

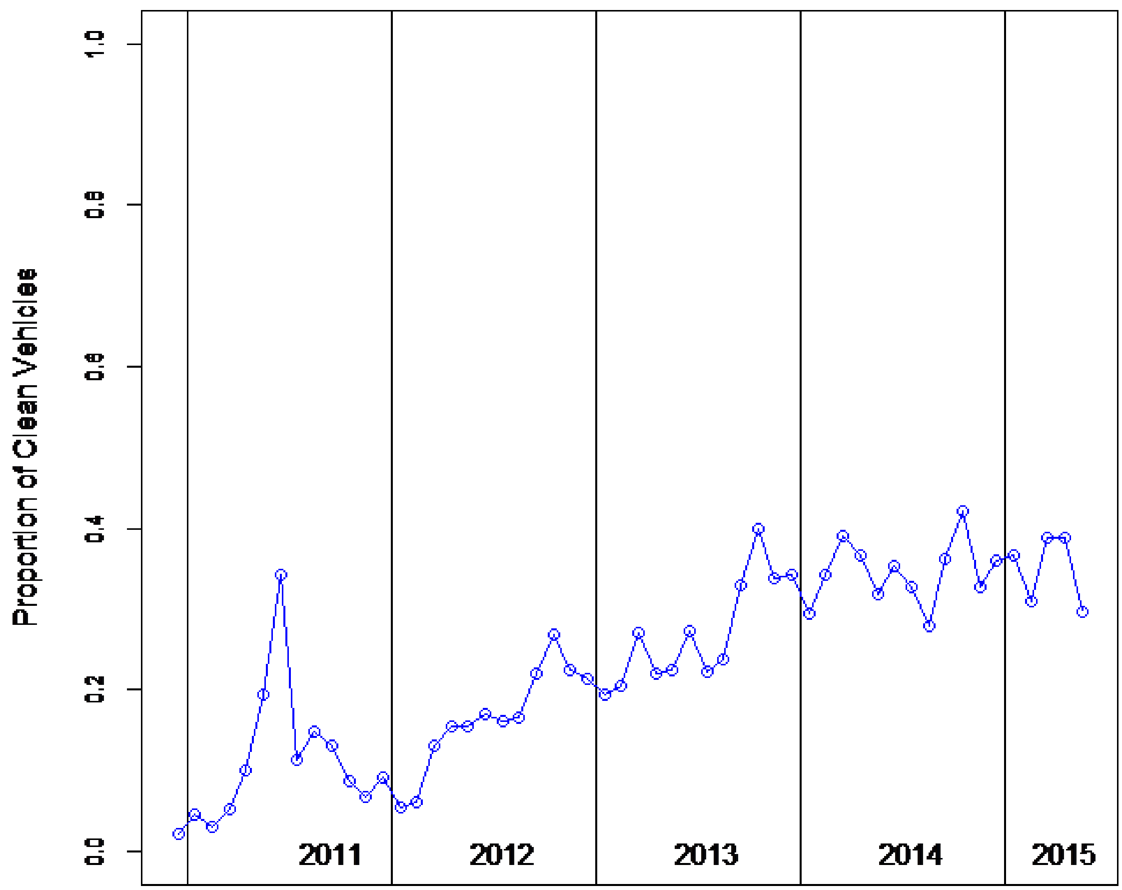
Figure 3-3: PEV and HEV Sales as a Proportion of All California New Vehicle Sales (Dec 2010 – May 2015)



Source: IHS 2010-2015

PEVs also make up a growing share of the clean-vehicle market (PEVs and HEVs). Statewide, we find that PEVs made up approximately 35% of all new clean vehicle sales in 2014 and 2015. In other words, PEV monthly sales now represent about one-half of HEV monthly sales (Figure 3-4). This proportion grew steadily between 2011 and 2013, stabilizing in 2014 and 2015. This is important because it suggests that PEVs are expanding the set of a clean vehicles and may soon gain parity with HEVs in terms of market share.

Figure 3-4: PEV Sales as a Proportion of All California New Clean Vehicle Sales (Dec 2010 – May 2015)

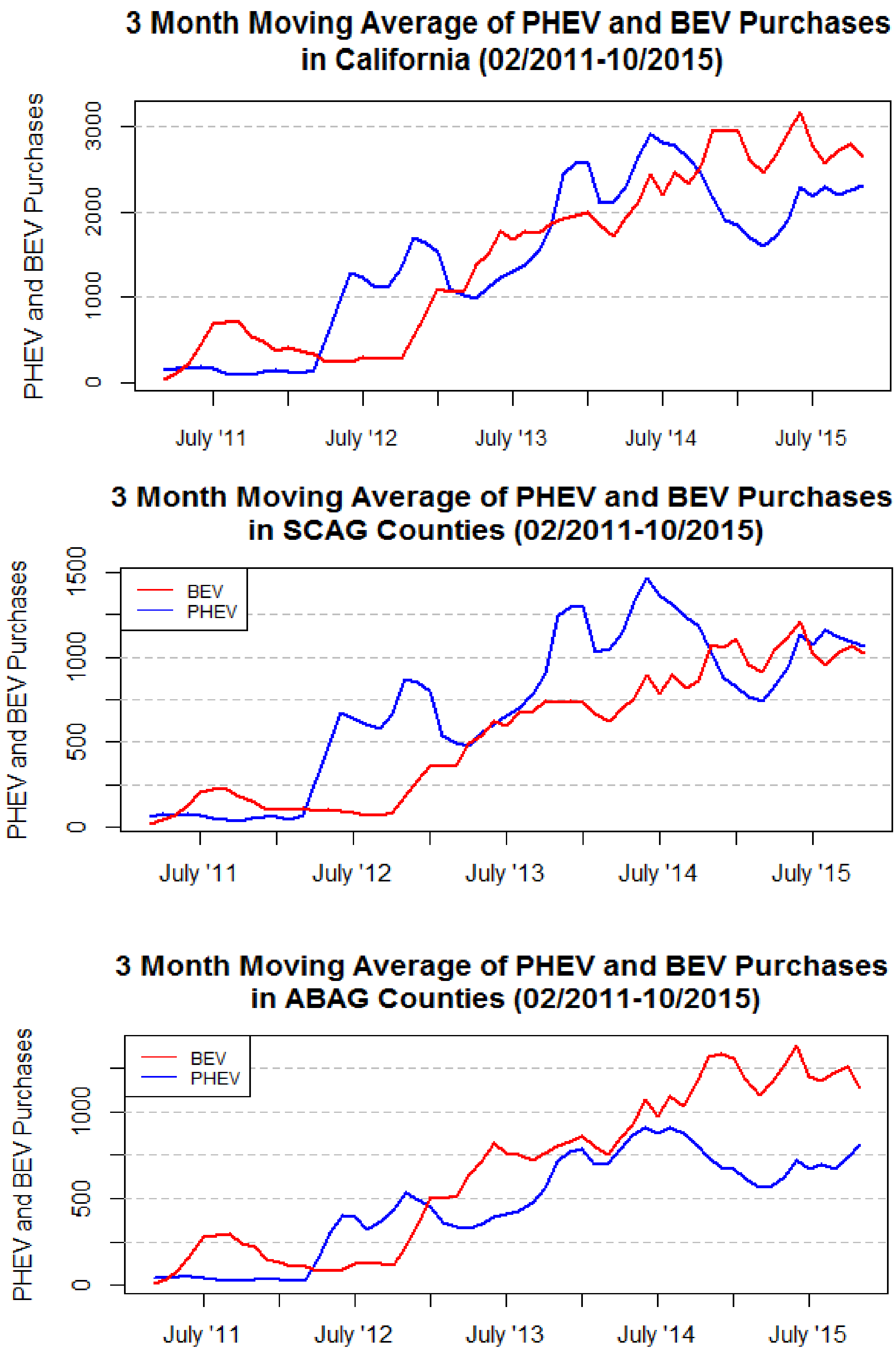


Source: IHS 2010-2015

Trend 3: PHEV and BEV Sales Trend together with Some Regional Variation

Although sales of both BEVs and PHEVs have grown rapidly in California since 2010, sales of the two types of vehicles have followed different trajectories. Figures 3-5A, 3-5B and 3-5C show the three-month moving average of BEV and PHEV registrations across all of California, the Southern California Association of Governments (SCAG) region and the Association of Bay Area Governments (ABAG) region respectively. These figures suggest three main takeaways. First, across all California regions, BEVs and PHEVs grew together until the summer of 2014, after which PHEV sales declined and BEV sales roughly remained flat. This trend may be driven by the continued strength in Tesla Model S sales combined with the fall in demand for the Prius Plug-in. Second, there is significantly more seasonality in PHEV sales than BEV sales. Third, BEVs are more frequently purchased in the Bay Area, and PHEVs are more popular in Southern California than they are in the Bay Area.

Figure 3-5A, 3-5B, 3-5C: 3 Month Moving Averages of PHEV and BEV Purchase

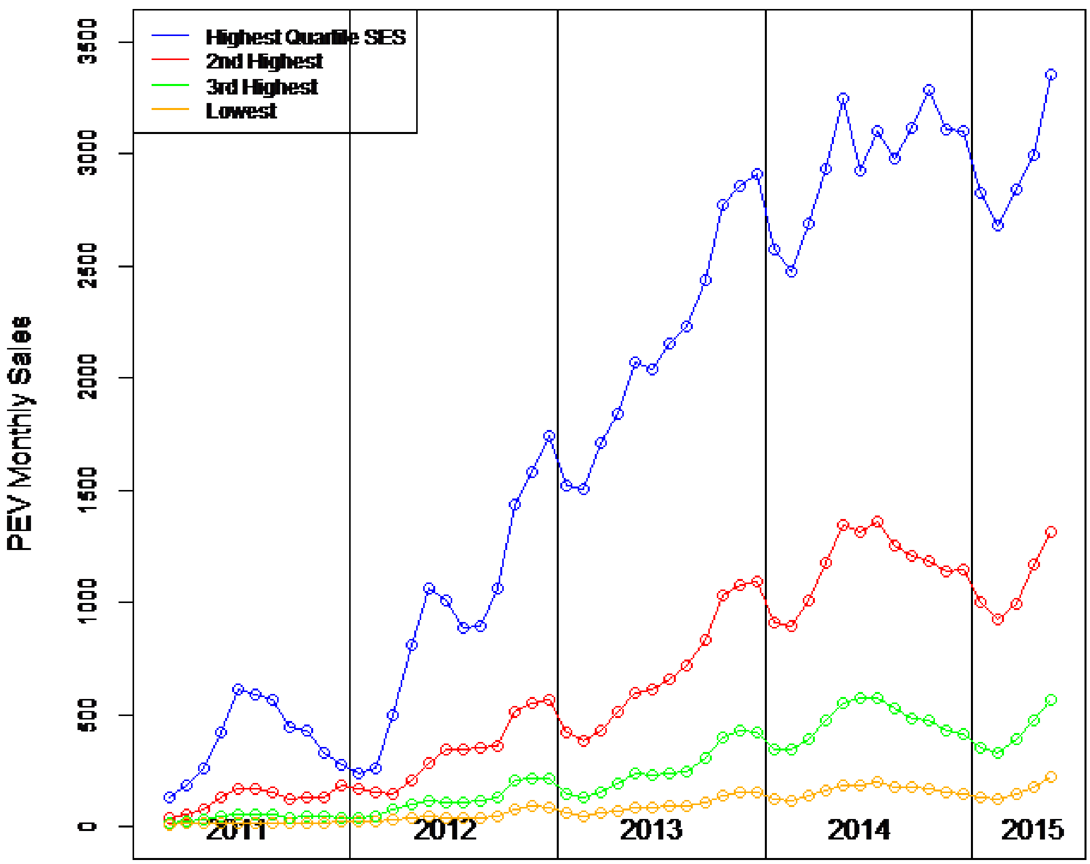


Source: IHS 2010-2015

Trend 4: PEV Purchases Have Been Disproportionately Concentrated in High-Socioeconomic Status Census Tracts

We created a socioeconomic status (SES) index [13]based on household incomes and education levels provided in the American Community Survey (U.S. Census) data. Using this index, we can describe how PEV adoption varies across each SES quartile.[14] This approach divides all households into four groups or quartiles: the top 25%, the upper-middle 25%, bottom-middle 25%, and bottom 25% in terms of their SES. We see from Figure 3-6 that households in the highest SES quartile had purchased almost three times the number of PEVs by 2014 as those in the second-highest SES quartile and over 10 times the number of PEVs purchased by households in the bottom quartile.

Figure 3-6: PEV Monthly Sales in California by Tract SES Quartile: 3 Month Moving Average (Dec 2010 – May 2015)



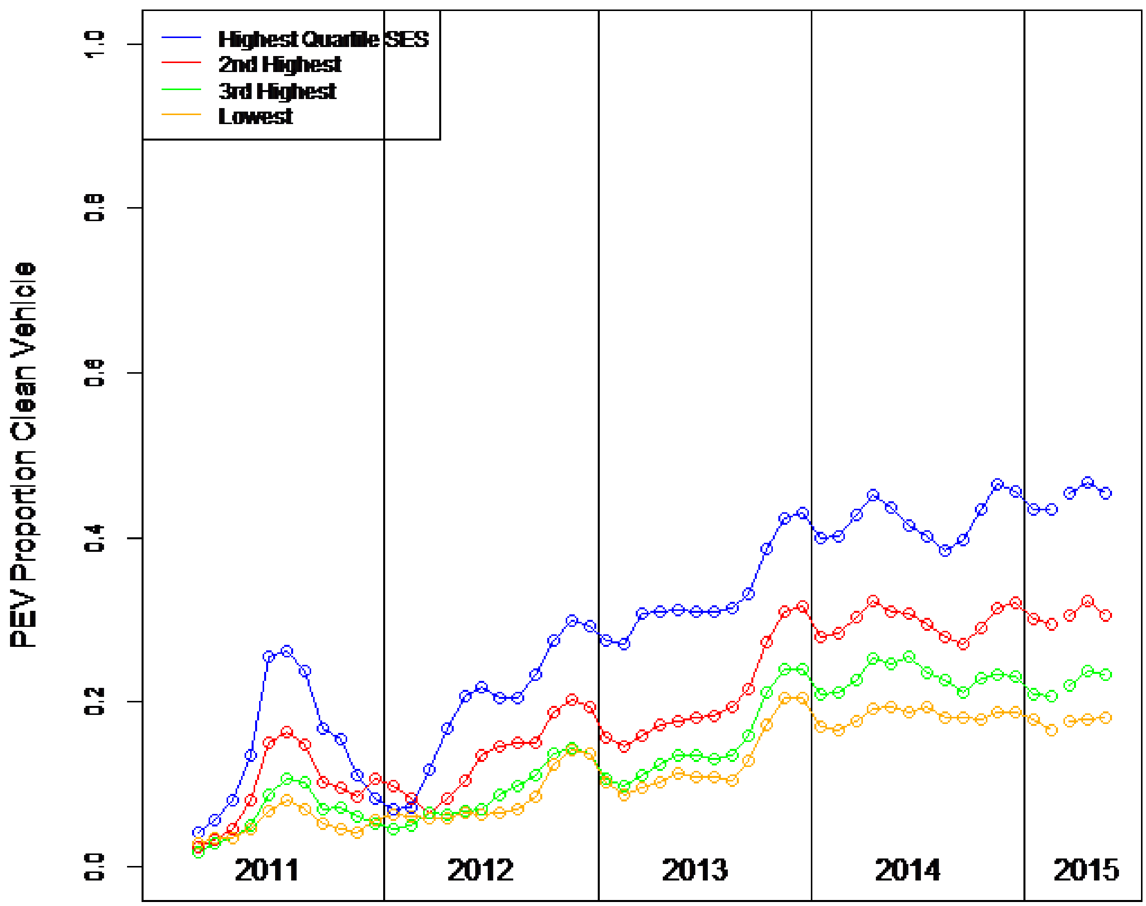
Source: IHS 2010-2015

[13] The index was created by standardizing for all census tracts:
1) Percent of households earning more than 200k a year
2) Median home value
3) Percent of individuals over 25 with more than a bachelor degree

[14] The first quartile group is made up of the households that rank in the top 25% based on the SES index. The second quartile is made up of the households ranked in the upper-middle 25%. The third quartile includes the households that fall in the bottom-middle 25% based on the SES index. Finally, the fourth quartile is the grouping of households that rank in the bottom 25%.

An observer might conjecture that these trends were driven by differences in propensity to purchase new vehicles more generally. However, our analysis of the PEV share of clean vehicle purchases across different quartiles suggests that other factors are at play like access and cost of infrastructure and cost differences between PEVs and Hybrids. Figure 3-7 shows PEVs made up 46% of all new clean vehicle purchases in census tracts in the top SES quartile. However, only 18% of clean vehicle-buying households purchase PEVs in census tracts in the bottom SES quartile. This socioeconomic variability in the propensity to purchase PEVs relative to hybrids appears to be growing over time and is explored further in Chapter 4.

Figure 3-7: PEV Proportion of Monthly Clean Vehicle Sales in California by Tract SES Quartile 3 Month Moving Average (Feb 2011 – May 2015)



Source: IHS 2010-2015

In Table 3-2, we examine the characteristics of these neighborhoods more closely. We first rank order all census tracts in the state by how many PEVs are purchased per 1,000 households, enabling us to identify those tracts in top, upper-middle, bottom-middle, and bottom quartile (groupings of 25%). Table 3-2 shows that the top, upper-middle, bottom-middle and bottom quartiles differ for key variables associated with PEV uptake.

Several major patterns emerge. First, tracts in the highest quartile of PEV purchases are much wealthier than all other tracts, with more than 4 times the number of households earning over $200,000 and houses worth over $1 million relative to tracts in the third quartile. Second, tracts in the highest purchase quartile have a higher proportion of adults with graduate degrees as well as a relatively large portion of workers in information-centric industries like Management and Information Technology. Third, tracts in the highest quartile were slightly less likely to vote against the repeal of AB32, indicating that they may have higher levels of environmentalism. Finally, tracts in the highest purchasing quartile are less dense, have more High-Occupant Vehicle (HOV) lane miles nearby and more single-family homes than other tracts. These results suggest that the census tracts purchasing the most PEVs differ from the median or average California tract on a number of important dimensions.[15] We next test these descriptive results through the creation of a predictive, statistical model in chapters 4 and 5.

Table 3-2 Quartile Analysis of Census tracts by PEV purchases per 1,000 households

	Bottom 25% of tracts (4th Quartile)	Lower-middle 25% of tracts (3rd Quartile)	Upper-middle 25% of tracts (2nd Quartile)	Top 25% of tracts (1st Quartile)
Tract Income Char.				
Median Home Value	224,659	307,619	435,939	676,864
Homes Worth > 1 Mil	1.3%	1.9%	4.1%	19.3%
Income Over $200K	1.3%	2.5%	5.7%	16.7%
Tract Demo. Char.				
Adults with Grad Degree	3.6%	6.5%	11.4%	21.3%
Workers in Mgmt, Info,	7.6%	10.2%	13.6%	18.4%
White	60%	61%	63%	68%
Tract Commute Characteristics				
>40 Min Commute	19%	20.7%	21.1%	21.5%
Population/sq mile	9933	9531	8268	5618
Vehicles Per Household	1.8	1.9	1.9	2.1
Other Characteristics				
Vote for AB32 Repeal	40.8%	38.9%	37.1%	35%
Single Unit Homes	73%	71.6%	72%	80%
HOV Miles in 5 Mi Radius	6.0	7.7	9.0	10.1

Source: ACS

Trend 5: Late-Adopting Tracts Are Not Catching Up to Early Adopters in PEV Sales

There is significant variation across census tracts in terms of when their first PEV was purchased. Among tracts whose residents had purchased at least one PEV by mid-year of 2015:

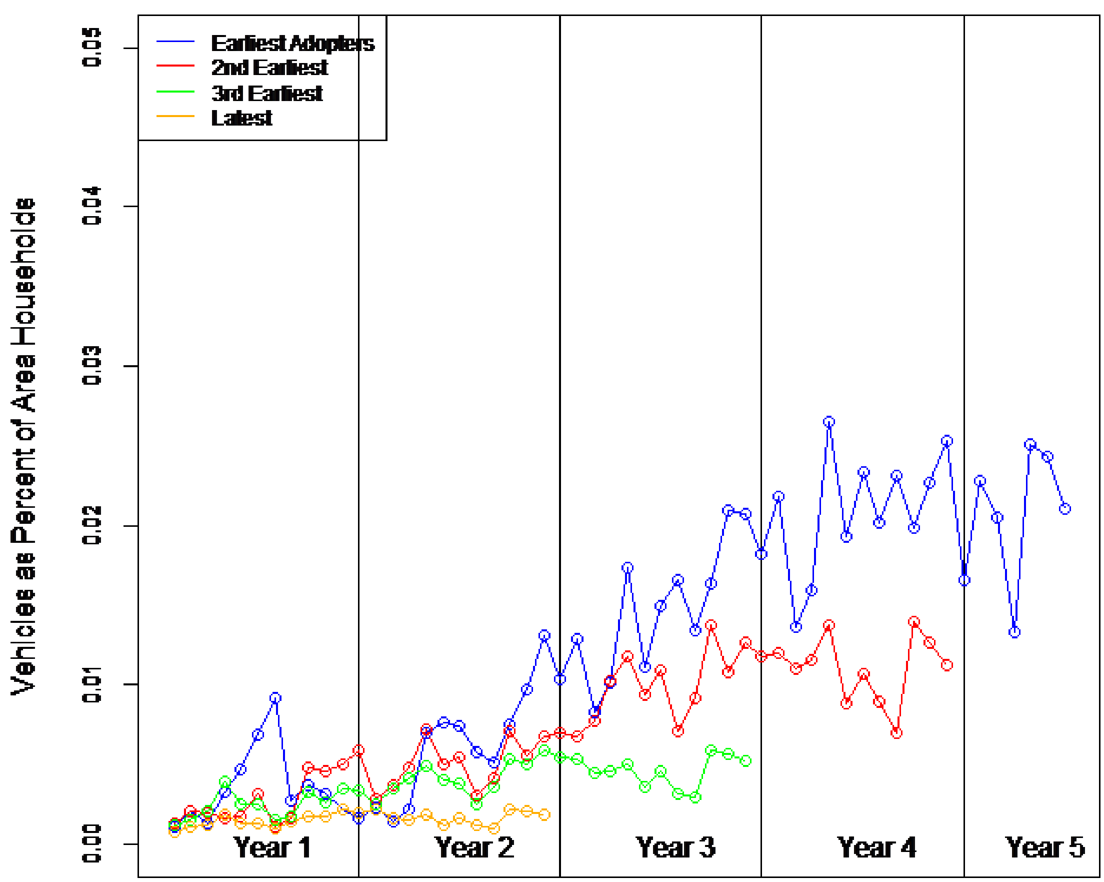
- 24% of tracts had at least one PEV purchase before July 2011,
- 50% had at least one PEV purchase before July 2012,
- 72% had at least one PEV purchase before July 2013, and
- 92% of tracts had purchased at least one PEV before June 2015

[15] The characteristics of the median California tract (at the 50th percentile) fall between the upper-middle and lower middle quartile values in Table 3-2.

Early-adopting census tracts not only purchased PEVs earlier; these tracts also ultimately exhibited a faster rate of PEV growth (relative to month of first purchase) and a higher PEV share of new clean vehicle purchases. Figure 3-8 shows monthly PEV sales as a percentage of all households in a tract by the timing of the first PEV purchase in the tract. Earliest adopter tracts purchased a PEV before July 2011, 2nd earliest purchased a PEV before July 2012, 3rd earliest purchased a PEV before July 2013 and latest adopting tracts purchased a PEV July 2013 or later.

Figure 3-9 shows that monthly sales as a percentage of tract group households are roughly similar across the four groups for the year after first adoption. However, beginning in the second year after first adoption, monthly sales as a percentage of total households rise much more quickly in the earliest adopting tracts. This trend suggests that later-adopting tracts are not "catching-up" to earlier adopters.

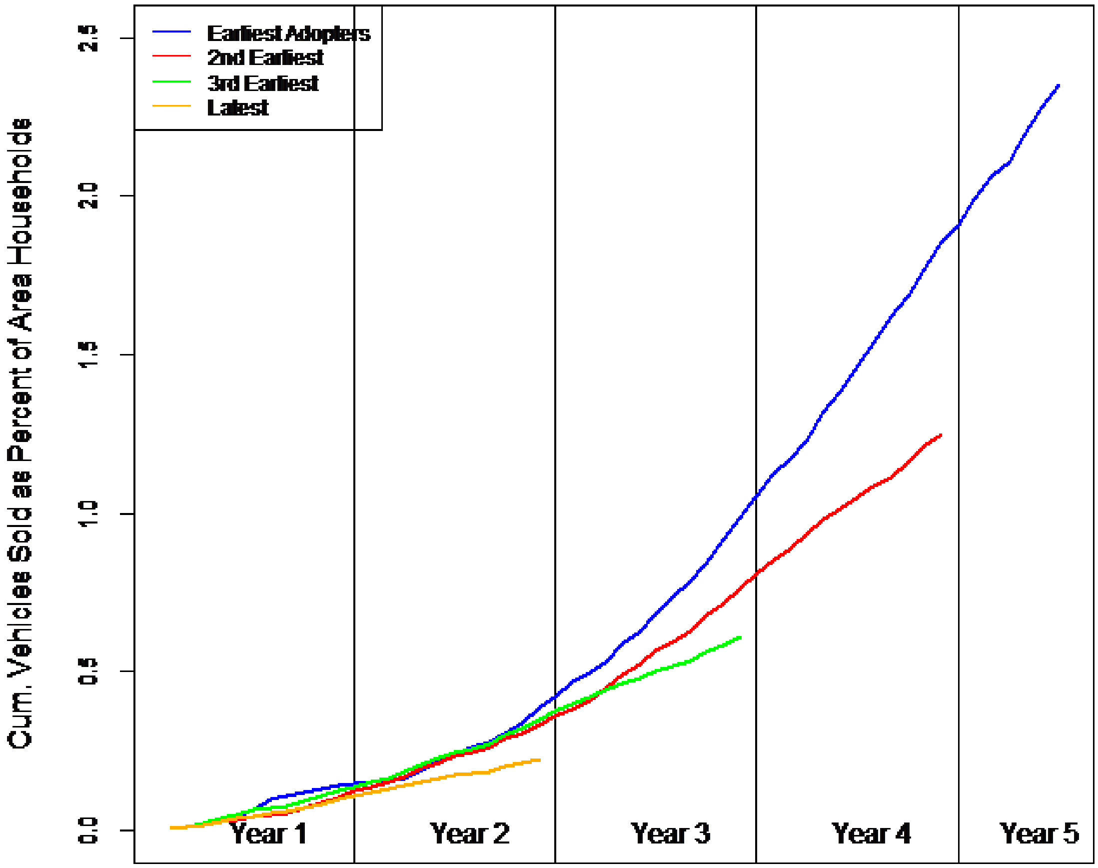
Figure 3-8: Monthly PEV Sales as a Percent of Households in California Census Tracts by Tract Adopter Status from Month of First Adoption



Source: IHS 2010-2015

This trend can be seen more clearly when looking at cumulative sales as shown in Figure 3-9. We observe that for the first 18 months after adoption, all adopter categories have roughly the same amount of cumulative sales. After 18 months, sales grow much more rapidly in earlier-adopting tracts.

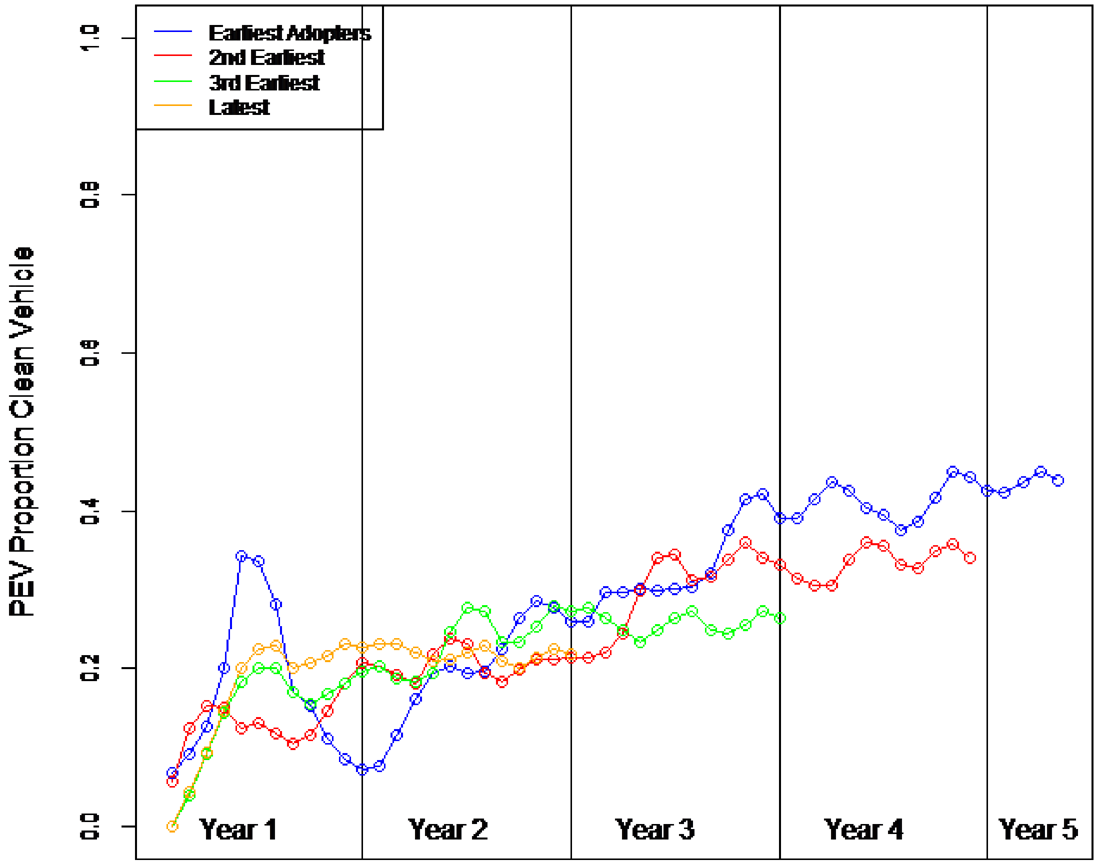
Figure 3-9: Cumulative PEV Sales as a Proportion of Households in California Census Tracts by Tract Adopter Status



Source: IHS 2010-2015

We see a similar, but less prominent pattern when looking at PEVs' share of clean vehicle sales. Figure 3-10, below, shows that 2 years after first PEV purchase, the PEV share of new clean vehicle purchases is relatively similar across adopter categories. However, after 3 and 4 years, the ratio of PEV to HEV purchases for tracts in the earliest-adopter groups is higher than later-adopting tracts.

Figure 3-10: PEV Proportion of Monthly Clean Vehicle Sales in California: 3 Month Moving Average (2011 – 2014)

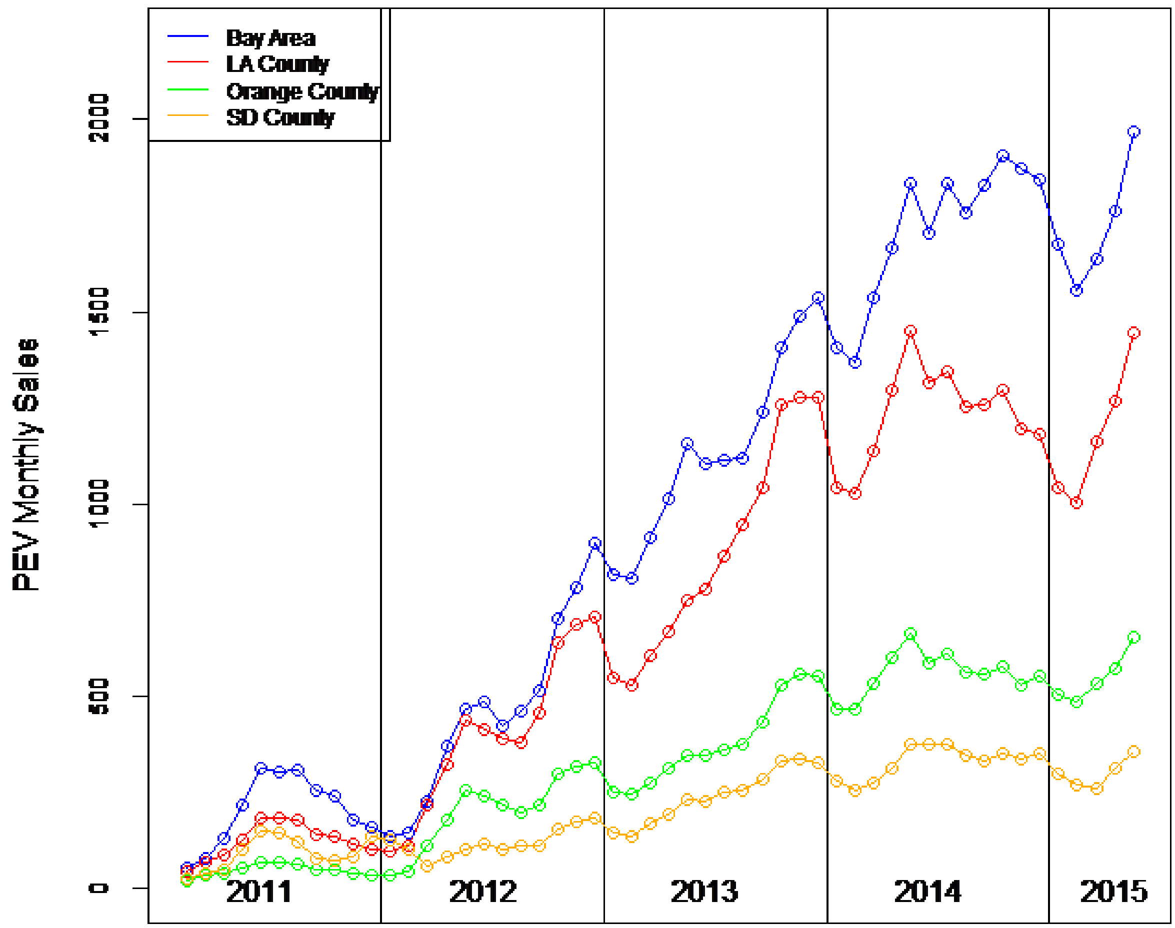


Source: IHS 2010-2015

Trend 6: PEV Sales Growth Varies Among Major Metropolitan Areas

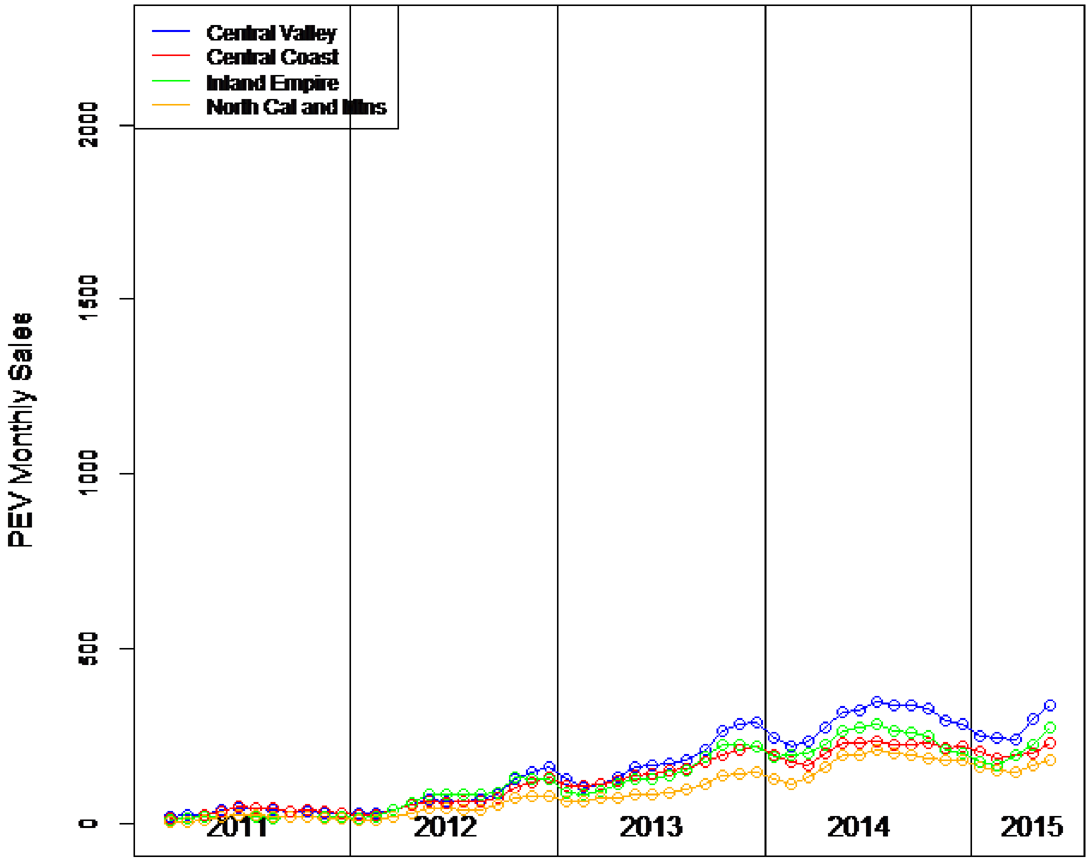
Metropolitan areas differ in socio-economic status and other factors, creating differences in PEV sales. Households in Los Angeles County and the Bay Area have purchased 62% of the state's PEVs, but make up only 44% of the state's households. Similarly, consumers in census tracts in the highest SES quartile purchased 65% of the state's PEVs, while making up only 28% of the state's households. These trends can be seen more clearly in Figures 3-11A and 3-11B. In Figure 3-11A, we can see that the vast majority of monthly PEV sales are concentrated in the Bay Area, Los Angeles County, Orange County and San Diego County. The rest of the state makes up only 19% of California's PEV sales despite containing 40% of California's households, including semi-rural regions as shown in Figure 3-11B, such as the Central Valley and Coast, Inland Empire and Northern Coast and Mountains.

Figure 3-11A: PEV Monthly Sales in California: 3 Month Moving Average (Feb 2011 – May 2015)



Source: IHS 2010-2015

Figure 3-11B: PEV Monthly Sales in California: 3 Month Moving Average (Dec 2010 – May 2015)

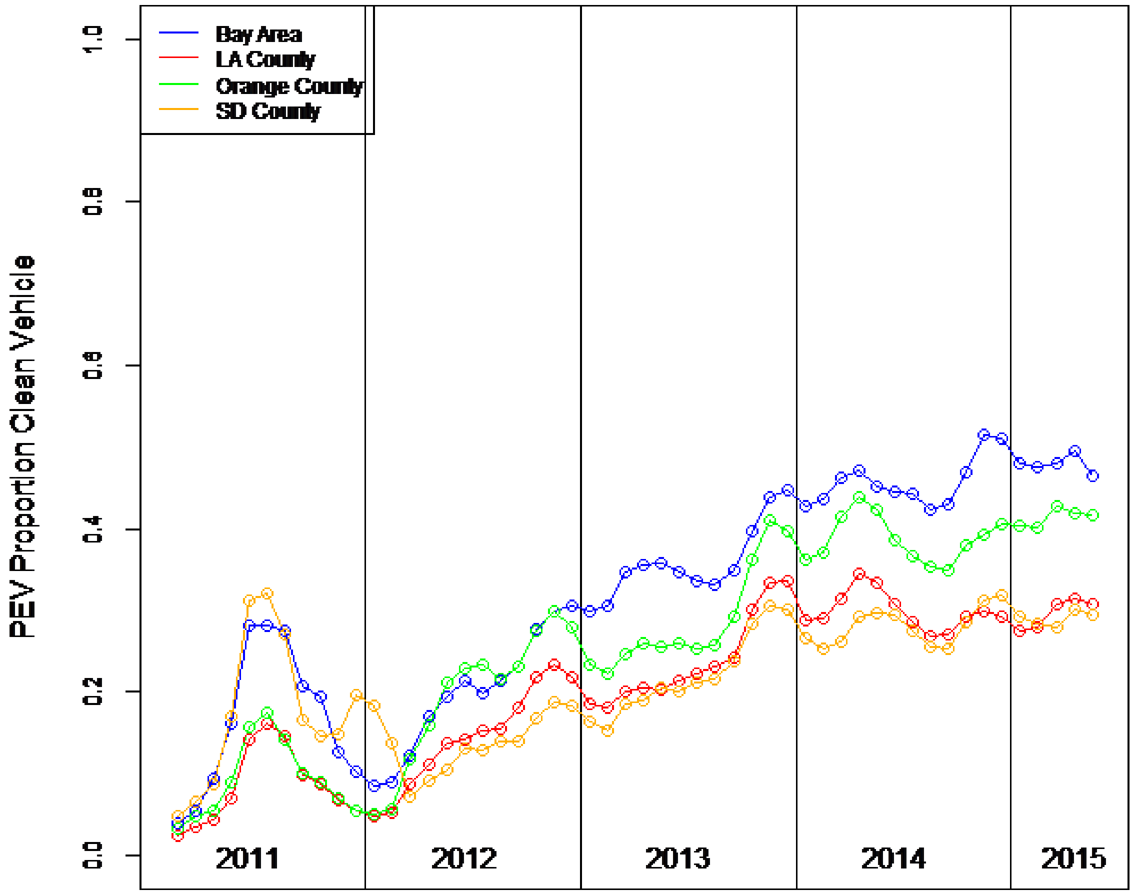


Source: IHS 2010-2015

PEV's market share of clean vehicle sales varies substantially across regions and consumer types. For instance, by May 2015 PEVs made up approximately half of all new clean vehicle purchases in the Bay Area, but only a little more than a quarter of new clean vehicle purchases in Los Angeles and San Diego counties [Figure 3-12].

This regional and SES variation in the make-up of the clean vehicle market suggests that there may be constraints to PEV ownership present in Southern California and lower-SES tracts that do not exist in the Bay Area and among more affluent consumers.

Figure 3-12: PEV Proportion of Monthly Clean Vehicle Sales in California by Region: 3 Month Moving Average (Feb 2011 – May 2015)



Source: IHS 2010-2015

Trend 7: Within Major Metropolitan Areas PEV Sales are Concentrated within Specific Neighborhoods.

Figures 3-13, 3-14, and 3-15 show maps of new PEV purchases per 1,000 households in census tracts in California, Los Angeles and the Bay Area respectively. Figure 3-13 makes it clear that new PEV purchases have largely been confined to California coastal regions. Figures 3-14 and 3-15 show that even within these regions, purchases have been concentrated in a relatively small number of neighborhoods.

Figure 3-13 PEVs/1000 Households in California

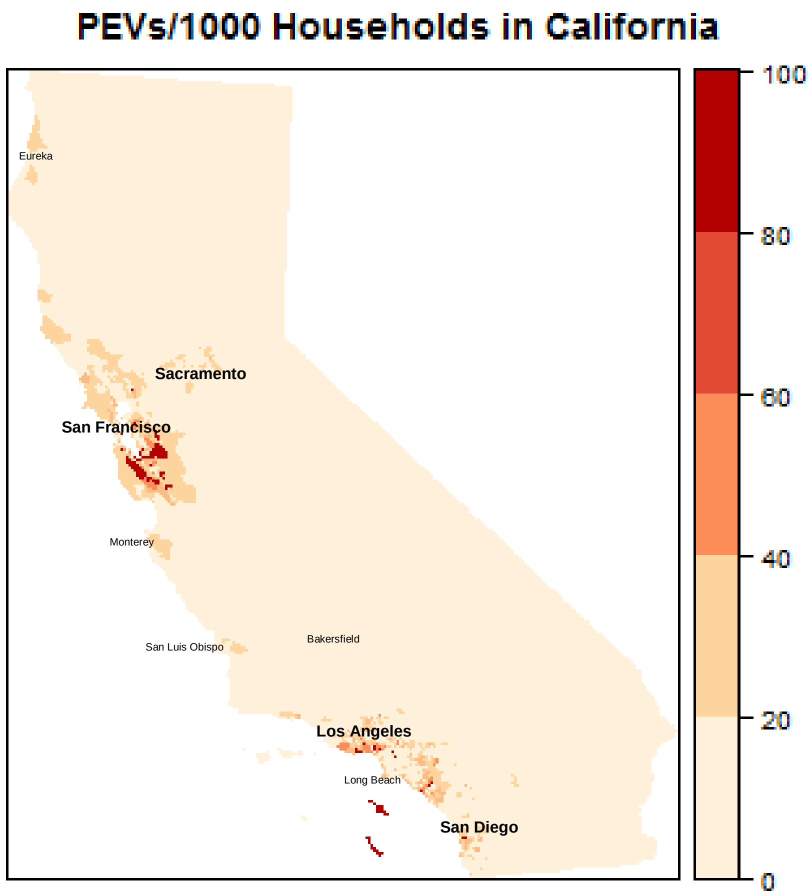


Figure 3-14 PEVs/1000 Households in Los Angeles

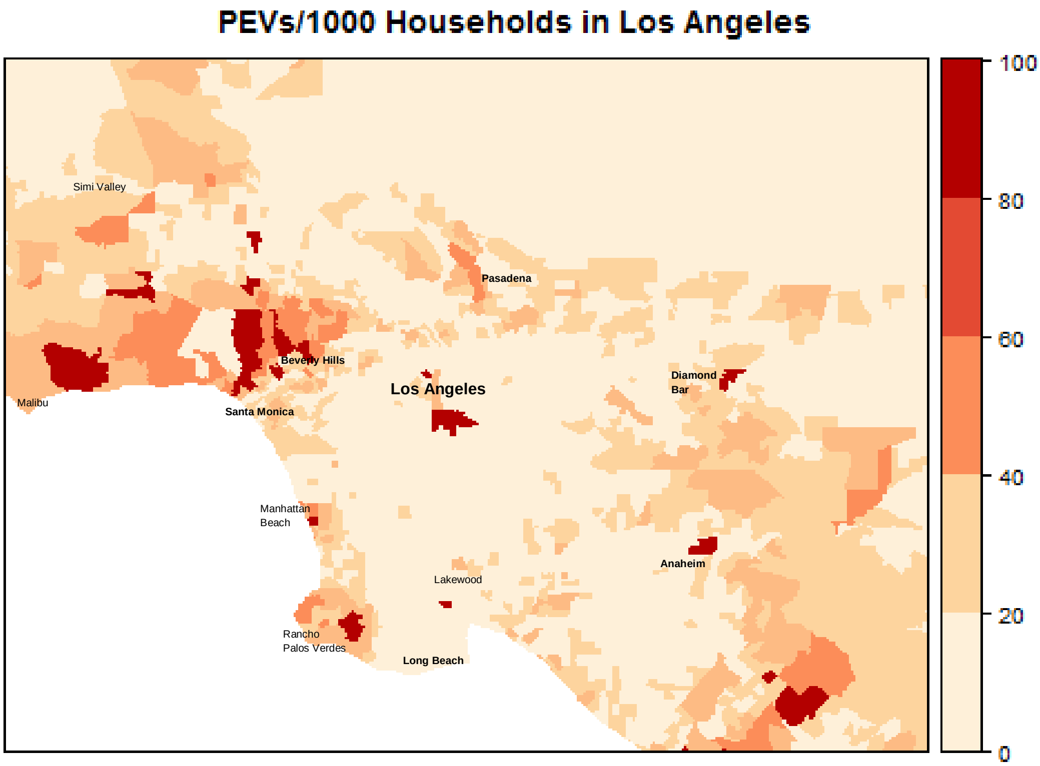
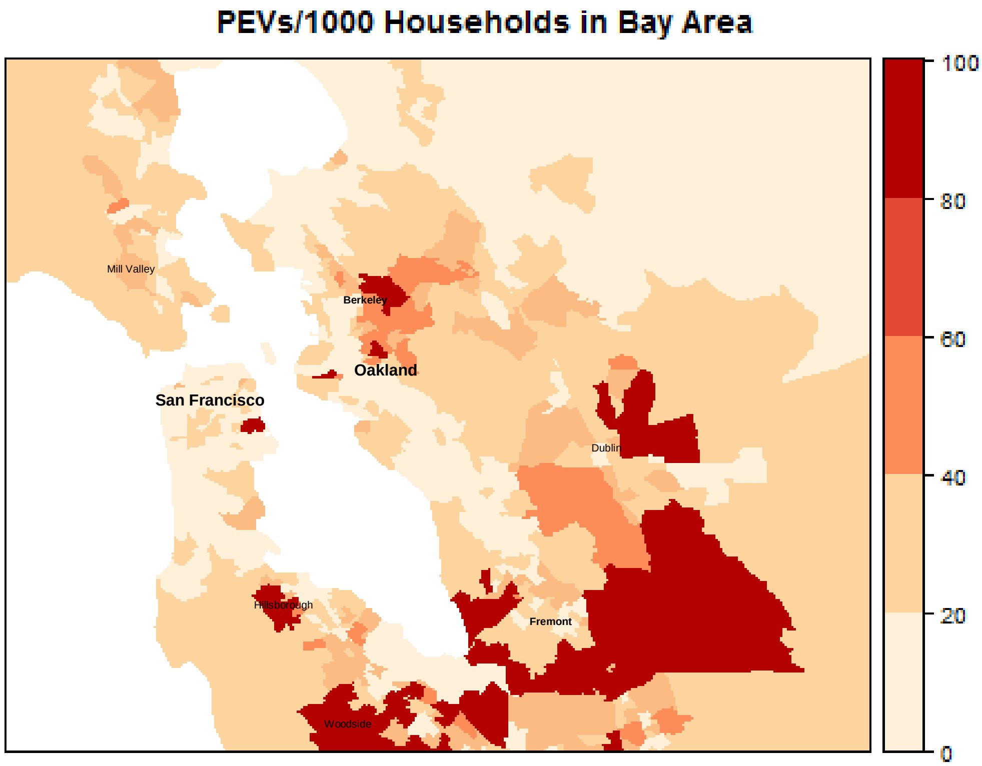


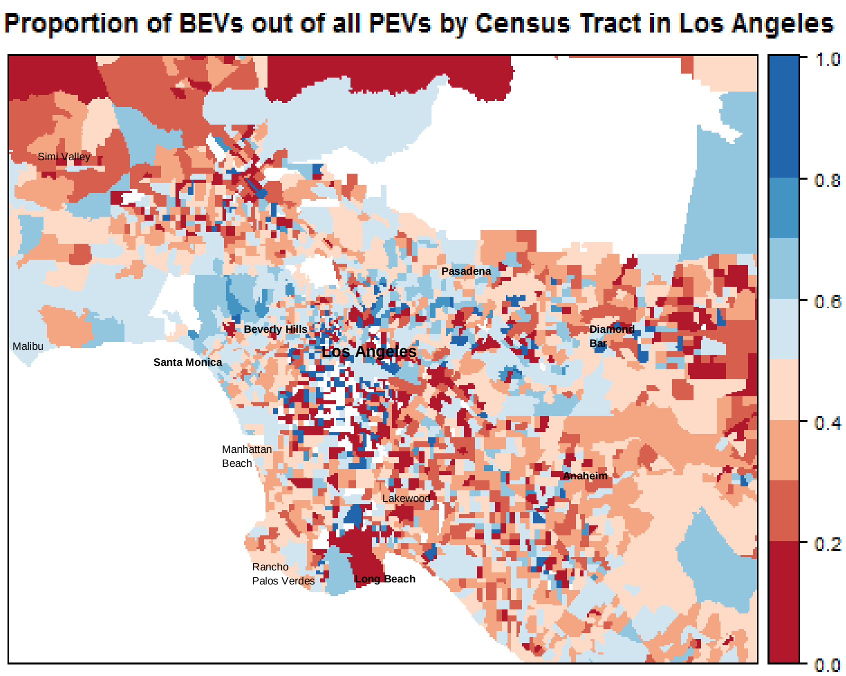
Figure 3-15: PEVs/1000 Households in Bay Area

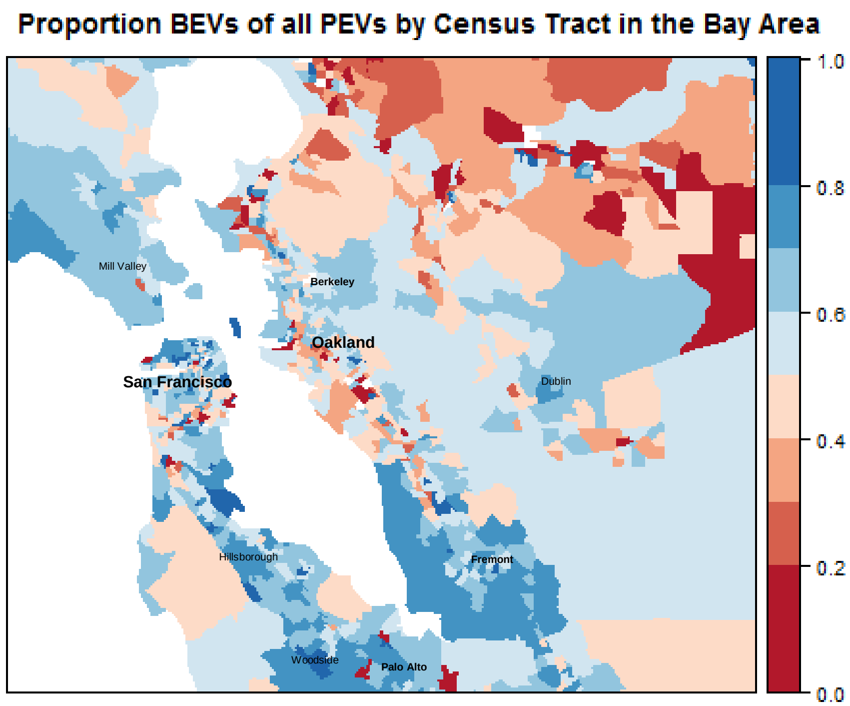


Trend 8: Relative BEV and PHEV Sales Are Also Geographically Concentrated within Metropolitan Areas

Figures 3-16 and 3-17 map the proportion of total PEV registrations by census tracts that are BEVs. These maps are consistent with the evidence from Figure 3-12; Bay Area census tracts are much more likely to have more BEVs than PHEVs. However, these maps also provide some suggestive evidence that BEVs are clustered in higher-income, suburban tracts. For instance, in Los Angeles, we can see that the only areas with a majority of BEVs are wealthy neighborhoods around Santa Monica, the Hollywood Hills and Altadena. Similarly, in the Bay Area, BEVs are especially concentrated in the wealthy suburbs of Silicon Valley and Marin County, while PHEVs are more concentrated in relatively less-affluent areas south of San Francisco.

Figures 3-16 and 3-17: The Proportion of BEVs Relative to PHEVs by Census Tracts





Chapter 4: Predicting Sales of Plug-in Electric Vehicles

While our analysis in Chapter 3 suggested that neighborhood and household socio-economic characteristics were correlated with PEV purchases, we did not systematically compare how much of the observed differences in plug-in electric vehicles (PEV), battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) sales across neighborhoods can be explained by these factors. In the first half of this chapter, we answer these questions using advanced statistical techniques.

4.1 Predicting PEV Purchases Across Census Tracts

In this section, we use statistical models to identify the distinctive characteristics of households in neighborhoods (e.g., census tracts) which have purchased PEVs between 2010 and 2015 in California.

We will look at the following factors, each of which will have a different outcome (or dependent) variable of interest. First, we want to explain which neighborhood characteristics are associated with an increase or a decrease in the concentration of PEVs purchased. The dependent variable of interest for this analysis will be PEVs purchased per 1,000 people. Second, we test whether the factors that we associated with high concentrations of PEV purchases might mistakenly just be capturing neighborhoods that tend to purchase new cars. We compare our PEV model and a model of non-PEV new car purchases in order to show how distinctive the estimated PEV neighborhood factors are.

Third, we identify which factors increase and decrease the ratio of BEV purchases to PHEV purchases across different neighborhoods. Our dependent variable in this model is the ratio of BEVs to PHEVs sold per month per neighborhood. Lastly, we estimate a model that correlates neighborhood factors with the sale of used PEVs. Our dependent variable in this model is the number of used PEVs sold per 1,000 households in 2015.

To explain variation in the dependent variables discussed we will employ a very large set of explanatory variables, most of which come from the American Community Survey (collected by the US Census Bureau). This data source contains over 200 different households and neighborhood characteristics. In addition, we employ explanatory variables associated with i) political attitudes, ii) census tract proximity to high-occupancy vehicle [HOV] lanes, iii) publicly-accessible charging stations within a census tract, and iv) gasoline and electricity prices at the metropolitan service area. These additional factors bring our total set of explanatory variables to over 300.

Our models will use these explanatory variables to evaluate three related questions:

1. Which variables are statistically correlated with PEV sales? In other words, which explanatory variables are we measuring with enough statistical precision to be confident there is positive or negative correlation with PEVs purchased?

2. What is the size (and sign) of the correlation between each explanatory variable and the quantity of PEVs purchased? In other words, how much does each explanatory variable contribute to the observed variation of PEVs purchased across neighborhoods?

3. How much of the total variation (or changes) of PEVs purchased across neighborhoods can the model explain? In other words, how much of a difference do we observe across neighborhoods in PEVs purchased that we can confidently attribute to changes in the explanatory variables for those neighborhoods?

Statistical Methods. With over 300 explanatory variables, we need a set of criteria for identifying the most important neighborhood factors that are correlated with our outcomes of interest. In order to focus attention on the most important explanatory variables, we will use a modeling approach that is called Least Absolute Shrinkage and Selection Operator (LASSO) as proposed by Tibshirani (1996).

Although it is tempting to just put all predictors into the model, this may not be the best method for two reasons. First, predictive models can be what we call "overfitted." That is, putting more and more variables into the model may improve our prediction in this specific instance, but will actually make our prediction less-likely to be correct if we try to apply it in another setting (i.e. PEV sales next year). Second, in many cases only a few variables explain most of the differences between observations. Thus, adding more variables does not improve prediction very much, but makes the model more difficult to interpret.

LASSO is a statistical technique that helps us identify which variables have the most power to predict the outcome that we care about. Unlike basic regression, it balances assigning weights to variables to create the best possible prediction while imposing a penalty for adding additional variables. If a variable does not add enough explanatory power, LASSO will restrict its weight to be 0. For instance, in the classroom example, although in a random classroom students with red hair might be slightly taller, LASSO would likely assign this variable a weight of 0 because it explains very little of the overall differences in classroom height. In this way, LASSO regression can provide us with models that use only a small subset of possible variables, but still have very high explanatory power. Even better, LASSO provides ways to test how well the model is expected to perform in other contexts, helping protect against the overfitting problem described above. Using LASSO regression in this report, we are able to create models that well-predict which census tracts purchase PEVs while using only a small number of explanatory variables.

Overview of Results. We find that variables associated with different levels of household income, housing value (which is a good proxy for household wealth) and education are important explanatory variables. Also important are household commuting patterns, race and in a few instances access to HOV lanes. The reader should be aware that the following analysis also originally included explanatory variables representing changes in gasoline prices, electricity prices, political attitudes toward environmental protection and the local availability of public accessible charging stations. However, most of these variables were not statistically significant over the period that we studied and so were excluded from the LASSO model.

4.2 Results from the Models Predicting PEV Purchases Across Neighborhoods

We first explain which neighborhood characteristics are associated with an increase or a decrease in the concentration of PEVs purchased. The dependent variable of interest for this analysis will be PEVs purchased per 1,000 households per month.

We first used a penalized regression method (LASSO) to select the best predictors among more than 300 social, demographic, geographical and economic variables from the American Community Survey and other data sources. Using cross-validation, we found that the optimal model included over 100 variables and was able to explain over 75% of the variation in PEV sales as shown by the R-squared value associated with Model 4 in Table 4-1 below.[16] This full model is presented in Chapter 4-Appendix A. However, for ease of interpretation and display, we use an abbreviated model in this report. This abbreviated model is able to explain more than 73% of the variation in PEV purchases per capita in a sample while including only ten predictor variables. This means that over 85 variables, when measured with statistical precision, explain all together less than 5% of the observed variation across neighborhoods. Thus, an extended discussion of these variables is likely to distract from the more important focus on the 10 variables that explain over 73% of the observed differences across census tracts.

The main results of this model are shown in Table 4-1. Table 4-1 presents five LASSO models with progressively more variables that explain progressively more of the variation observed across neighborhoods. Each predictor variable has been standardized, so the coefficients can be interpreted as the expected change in the number of PEVs/1000 households of a 1 standard deviation increase for a given variable, holding all other factors constant.

Several important trends become immediately clear. First, as shown by Model 1 in Table 4-1, including only a tract's percent of households earning over $200,000 explains more than 65% (see the R-squared of .667 on Model 1, Table 4-1) of the variance in PEV purchases. A one standard deviation increase in the percent of households in a tract earning over $200,000 is

[16] The R-squared statistic describes how the total observed variation in PEV can be explained by the set of explanatory variables contained in each model. The estimated value of R-squared ranges in value from 0 to 1.00, denoting the set of estimated explanatory variables between zero and 100% of the observed variability in the PEV sales across neighborhoods. The higher the R-squared the more likely the estimated model will accurately predict changes in PEV sales.

associated with 12 more PEV purchases per 1,000 households. In other words, just knowing how many high-income residents are in each tract allows us to make a reasonable guess of how many PEVs that tract may have.

Second, looking at models 2 and 3 in Table 4-1, the three next most important predictor variables are median home value, percent of adults with masters' degrees and percent of households with income between $150,000-$200,000, all of which have positive effects. This further reinforces the idea that the socio-economic status of a tract's residents is the main predictor of PEV purchases. Third, we see that the percentage of households who are of Asian descent, percent of households who commute alone with incomes greater than $75,000 and those with local access to HOV lane mileage are important and positive predictors. This later result provides correlational evidence that the states' HOV permit program may be associated with PEV sales.

Table 4-1: Abbreviated Regression Models Predicting New PEV Purchases per capita

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
VARIABLES	**PEV/1000 HH**	**PEV/1000 HH**	**PEV/1000 HH**	**PEV/1000 HH**	**PEV/1000 HH**
Percent Income Over $200k	12.04***	9.414***	8.214***	6.733***	7.129***
	(0.170)	(0.252)	(0.277)	(0.337)	(0.325)
Median Home Value		3.361***	2.248***	1.661***	0.171
		(0.196)	(0.206)	(0.207)	(0.247)
Percent Adults with Master's Degree			1.591***	1.498***	1.516***
			(0.212)	(0.210)	(0.197)
Percent Income $150-$200k			1.513***	1.422***	1.462***
			(0.162)	(0.194)	(0.184)
Percent Homes Worth Over 1 Mil($)				1.743***	2.344***
				(0.275)	(0.263)
Median Rent				0.896***	0.521***
				(0.149)	(0.147)
Earn >$75k and Commute Alone				0.367*	0.197
				(0.205)	(0.199)
HOV Miles in 5 Mile Radius					1.728***
					(0.0899)
Percent Homes Worth $150-$300k					-0.901***
					(0.107)
Percent Asian					0.945***
					(0.116)
Constant	11.84***	11.84***	11.84***	11.84***	11.84***
	(0.0960)	(0.0930)	(0.0910)	(0.0898)	(0.0863)
Observations	7,855	7,855	7,855	7,855	7,855
R-squared	0.667	0.687	0.701	0.709	0.731

Source: American Community Survey 2013-2015; IHS 2010-2015

Standard errors in parentheses ***p<0.01, **P<0.05, *p<0.1

4.3 Analysis of Future PEV Sales in Early- Versus Late-adopting Neighborhoods

In Chapter 3 we showed that early-adopting neighborhoods not only purchased PEVs earlier; these neighborhoods also ultimately exhibited a faster rate of PEV purchase growth compared to late-adopting neighborhoods. In this analysis we explore how these patterns can be explained by two different hypotheses. First, these differences may be due to differences in the socio-economic characteristics of a neighborhood. Second, it may be that in early adopting neighborhoods, households are exposed to PEVs which may affect future sales of PEVs in these neighborhoods.

To evaluate these two hypotheses, we first show how well we can predict 2015 PEV purchases based on a tract's 2014, 2013 and 2012 purchases. We next add in variables representing the history of PEV purchases in each neighborhood to examine how much variation in the observed difference across neighborhoods they explain. Table 4-2 shows various specifications of a predictive model to estimate the number of PEVs/1000 Households sold between September 2014 and August 2015. We used the same LASSO regression model as in section 4.2 to select variables with the highest predictive power.

Table 4-2: Regression Models Predicting PEV Sales Based on Previous Sales Figures

VARIABLES	(1) PEV/1000 HH (09/14-08/15)	(2) PEV/1000 HH (09/14-08/15)	(3) PEV/1000 HH (09/14-08/15)
PEV/1000 HH (09/13-08/14)	3.305***	2.443***	2.303***
	(0.121)	(0.102)	(0.0989)
PEV/1000 HH (09/12-08/13)	0.916***	0.637***	0.631***
	(0.0931)	(0.0811)	(0.0815)
PEV/1000 HH (09/11-08/12)	0.299**	0.191*	0.197*
	(0.148)	(0.107)	(0.109)
Percent Income Over $200k		0.856***	0.636***
		(0.0859)	(0.0998)
Percent Income $150-$200k		0.811***	0.423***
		(0.0515)	(0.0630)
Median Home Value			0.161**
			(0.0726)
Median Rent			0.266***
			(0.0470)
Earn >$75k and Commute Alone			0.178***
			(0.0650)
Percent Adults with Master's Degree			0.136**
			(0.0643)
Percent Asian			0.490***
			(0.0390)
Constant	4.016***	4.016***	4.016***
	(0.0309)	(0.0288)	(0.0279)
Observations	7,855	7,855	7,855
R-squared	0.70	0.74	0.75
Source: American Community Survey 2013-2015; IHS 2010-2015			
Standard errors in parentheses ***p<0.01, **P<0.05, *p<0.1			

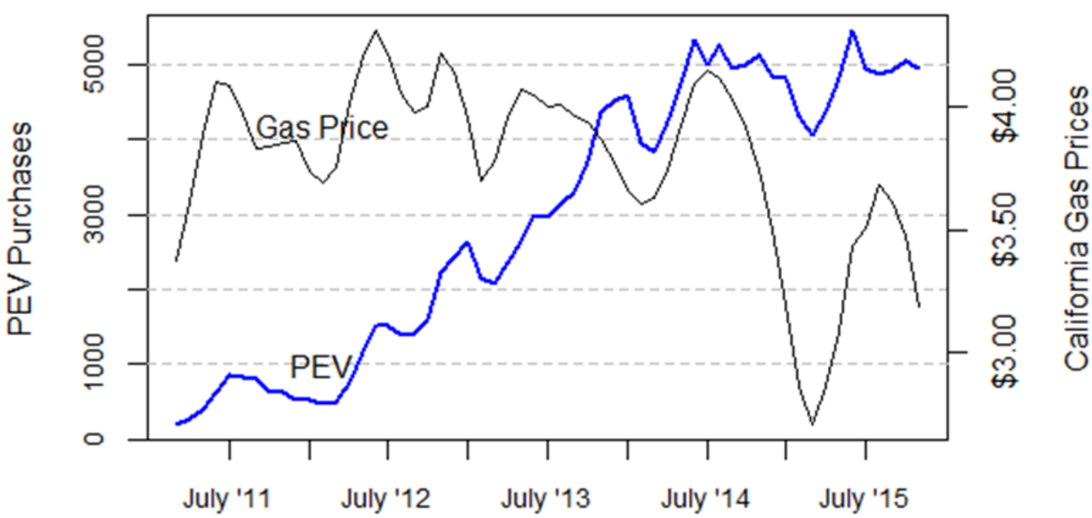
There are several major takeaways. First, we see in Model 1 of Table 4-2 that including prior sales over each of the past three years explains nearly 70% of the variance of Year 4 sales as shown by the R-squared in Model 1 of Table 4-2. Interestingly, sales in Year 1, Year 2 and Year 3 all enter significantly, suggesting that the speed of a tracts' adoption contains considerable information about the level of year sales. Second, as shown in Model 3, even after controlling for prior sales, several demographic variables still significantly affect Year 4 purchases. Further, these variables were mostly the same variables, with the same coefficient sign, as the ones included in the model first described in this chapter.

We see that the socioeconomic variables are statistically significant in Model 3even after accounting for PEV purchase history within each neighborhood. Therefore, both our hypotheses appear to be supported by these results. Our result suggests that PEV sales are growing more rapidly among higher SES tracts than lower SES tracts even after accounting for past trends. In other words, using just past trends alone to predict future sales would lead us to under-predict sales in high-income areas and over-predict sales in low-income areas.[17]

California Gasoline Prices and PEV Purchases. One major advantage of PEVs over internal combustion engine vehicles (ICE) are lower fuel costs. Thus, we may expect that as consumers' expectations of future fuel prices decrease, PEV purchases will also fall. Ideally, we would like to test this hypothesis by comparing zip-code or census tract level gasoline price changes with changes in PEV registrations. Unfortunately, our data from 2010 to early 2014 showed no correlation between gasoline prices and PEVs sales. This is most likely because there was so little variation in gasoline prices over this period as shown in Figure 4-1 below.

For later 2014 to 2015, when gasoline prices fell dramatically, we lack detailed data on gasoline prices. We are, however, able to compare trends in average state gasoline prices and average state PEV purchases. Figure 4-1 shows this comparison graphically. The fall in PEV sales and the fall in gasoline prices do appear to match up graphically, but we should be very careful in interpreting these results as both gasoline prices and PEV sales exhibit strong seasonality, which may lead to spurious correlations. Much more work is necessary before we could conclude that this relationship is causal.

Figure 4-1: Monthly PEV Purchases and Gasoline Prices in California



[17] These trends are largely robust to two changes in the model: using the log of PEV purchases as our dependent variable (and dropping tracts with no purchases).

4.4 Are We Identifying Predictive Variables Associated with PEV Purchases or New Car Purchases More Generally?

It is possible that the model above is identifying predictive variables of new car purchases that are not unique to PEV purchasers. For example, it is possible that the high predictive role of income and wealth help explain all new vehicle purchases and not just purchases of PEVs. To evaluate this we compare the results of our PEV model with that of a non-PEV new car model. The type of new purchases that we examine are those of new hybrid vehicles. If we find these two models to be different, we have some evidence that our prior PEV results are distinctive to PEVs. To undertake this comparison, we estimate a model that identifies the predictive variables correlated with new Hybrid-Electric Vehicle (HEV) purchases, where the dependent variable is HEVs per 1,000 households. If we find this model to be similar to the above PEV model, then our concern that we are predicting new car buyers rather than PEVs would persist. If the models are different then we can be more confident that we are identifying PEV-specific purchase patterns from other new vehicles.

The results of our analysis are shown in Table 4-3. There are several important differences between the HEV and PEV model. First, looking at Model 4 in Table 4-3, we can see that the HEV model is less successful in explaining total variance in HEV sales, suggesting that HEV sales are less correlated than PEV sales with observable tract characteristics. See that the model that explains most of the observed variation, Model 4 in Table 4-3 is able to explain only 43 percent, as shown by the R-squared value of .43, of the observed variation across neighborhoods as compared with 73 percent for the PEV model above. Our model of PEV sales performs much better, in terms of explaining differences in PEV sales, than does the new hybrid model.

Second, although some of the socioeconomic variables that are correlated with PEV sales are similar in the new hybrid model (see the variables concerned with income levels, home and rental value in Model 4 of Table 4-3), their relative importance differs significantly. Third, several new variables emerge from the LASSO hybrid analysis. The most important predictor variable for new hybrid purchases is the percent of adults with only a BA, perhaps suggesting the importance of a tracts' middle-class (relative to elite) population when considering number of HEV purchases. We also find (in order of importance) that 1) naturalized (foreign-born) households, 2) percent of households that work in the information industry, and 3) percentage who have a professional degree have a positive correlation with hybrids purchased per 1,000 households, while 4) the percent below the poverty level has a negative correlation.

Table 4-3 Regression Models Predicting HEV Sales per capita

VARIABLES	(1) HEV/1000 HH	(2) HEV/1000 HH	(3) HEV/1000 HH	(4) HEV/1000 HH
Percent Adults with only BA	9.893***	6.745***	5.199***	3.416***
	(0.436)	(0.410)	(0.384)	(0.463)
Median Home Value	9.773***	4.822***	2.189***	1.977***
	(0.490)	(0.530)	(0.512)	(0.516)
Percent Income Over $200k		5.255***	7.188***	5.346***
		(0.568)	(0.508)	(0.599)
Median Rent		5.572***	4.727***	3.357***
		(0.437)	(0.436)	(0.461)
Percent Income $150-$200k				0.829**
				(0.407)
Percent Foreign-Born Pop Naturalized			4.921***	5.113***
			(0.292)	(0.294)
Percent Work in Information Industry			3.526***	3.629***
			(0.271)	(0.268)
Percent in Poverty				-0.845***
				(0.278)
Percent Adults with Prof Degree				2.455***
				(0.460)
Percent w/ Income $125-$150k				1.799***
				(0.411)
Earning >$75k and Commute Alone				0.673*
				(0.385)
Constant	34.27***	34.27***	34.27***	34.27***
	(0.280)	(0.272)	(0.264)	(0.262)
Observations	7,855	7,855	7,855	7,855
R-squared	0.354	0.391	0.425	0.432

Source: American Community Survey 2013-2015; IHS 2010-2015

Standard errors in parentheses ***p<0.01, **P<0.05, *p<0.1

4.5 A Deeper Exploration of the Neighborhood Determinants of Purchasing BEVs versus PHEVS

In Chapter 3 we showed that BEV purchases relative to PHEV purchases vary over time both within the state and across regions while noting that the ratio of BEVs to PHEVs appeared to be higher in the San Francisco Bay Area compared to the Los Angeles region. (See Figures 3-16 and 3-17) To explore the determinants of these trends more systematically, we ran a LASSO regression searching for the best predictors of the proportion of BEVs in a census tract using more than 300 covariates from the US Census.

Table 4-4 summarizes the results. This table shows that highly-educated, high-income households working in management industries have a higher propensity to purchase BEVs relative to PHEVs. For instance, in Model 4 which is most complete, each additional increase of ten percentage points to the value of houses worth over $1 million in a census tract is associated with a 1.5 percentage point increase in the proportion of BEVs registered. As one might expect, long commutes are highly associated with a preference for PHEVs; many BEV models have insufficient range to cover a round trip commute longer than an hour. A ten percentage point increase in households commuting more than an hour is associated with a 6 percentage point decrease in the proportion of BEVs registered.

Finally, it is important to note that this model does a relatively poor job of predicting the proportion of BEVs in a census tract; our best model only explains 7% of the total variance. This low predictive power may be because tracts with low numbers of total new vehicle registrations will tend to have either all or no BEVs (i.e., a tract with 1 registration must have a BEV count of either 0 or 1). Accordingly, we re-estimate these models for only census tracts with ten or greater PEV registrations. Table 4-5 shows these results for 2010-2014. The results are qualitatively the same although the predictive power has increased (partially caused by fewer observations).

Table 4-4: Predictors of the Proportion of BEVs in a Census Tract

VARIABLES	(1) Prop. BEV	(2) Prop. BEV	(3) Prop. BEV	(4) Prop. BEV	(5) Prop. BEV
Percent w/ Grad Degree	0.462***	0.387***	0.258***	0.183***	0.127***
	(0.0247)	(0.0255)	(0.0331)	(0.0330)	(0.0371)
Percent Commute Longer Than 1 Hr		-0.607***	-0.608***	-0.608***	-0.601***
		(0.0465)	(0.0464)	(0.0461)	(0.0464)
Percent Houses Worth >1 mil			0.134***	0.159***	0.152***
			(0.0160)	(0.0161)	(0.0160)
Percent Asian				0.166***	0.161***
				(0.0162)	(0.0162)
Percent Working in Management					0.267***
					(0.0831)
Constant	0.401***	0.467***	0.473***	0.458***	0.445***
	(0.00500)	(0.00737)	(0.00748)	(0.00778)	(0.00919)
Observations	7,303	7,303	7,303	7,303	7,303
R-squared	0.034	0.057	0.062	0.071	0.072

Source: American Community Survey 2013-2015; IHS 2010-2015

Standard errors in parentheses ***p<0.01, **P<0.05, *p<0.1

Table 4-5: Predictors of the Proportion of BEVs in Census Tract w/ > 10 PEV Registrations

VARIABLES	(1) Prop. BEV	(2) Prop. BEV	(3) Prop. BEV	(4) Prop. BEV	(5) Prop. BEV
Percent w/ Grad Degree	0.483***	0.390***	0.255***	0.207***	0.134***
	(0.0211)	(0.0214)	(0.0273)	(0.0271)	(0.0298)
Percent Commute Longer Than 1 Hr		-0.692***	-0.694***	-0.702***	-0.682***
		(0.0406)	(0.0403)	(0.0398)	(0.0399)
Percent Houses Worth >1 mil			0.117***	0.144***	0.137***
			(0.0131)	(0.0131)	(0.0130)
Percent Asian				0.169***	0.165***
				(0.0138)	(0.0136)
Percent Working in Management					0.367***
					(0.0643)
Constant	0.397***	0.475***	0.484***	0.461***	0.441***
	(0.00458)	(0.00653)	(0.00658)	(0.00688)	(0.00793)
Observations	4,034	4,034	4,034	4,034	4,034
R-squared	0.099	0.165	0.177	0.206	0.212

Source: American Community Survey 2013-2015; IHS 2010-2015

Standard errors in parentheses ***p<0.01, **P<0.05, *p<0.1

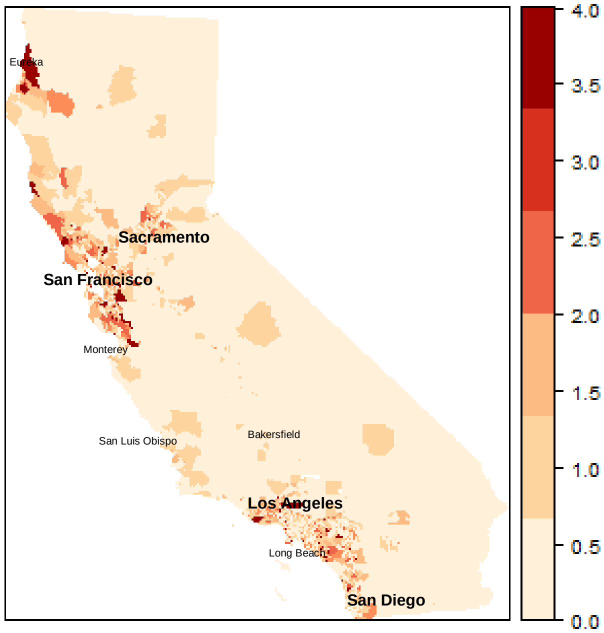
4.6 An Early Look at the Neighborhood Determinants of Used PEVs

As we showed in our earlier analysis, PEV purchases are more common in high SES census tracts. However, to design good PEV infrastructure policies, it is not sufficient to know who is purchasing these new vehicles. It is also necessary to know who is purchasing used PEVs. Further, examining differences between new and used PEV purchasers can provide some insight into barriers to the adoption of new PEV vehicles.

In this section we examine purchases of used PEVs in California between January and October 2015. In total, there were 8,572 purchases of used PEVs in California during this time period, representing about 5% of the total new PEVs sold and leased in California since December 2010.

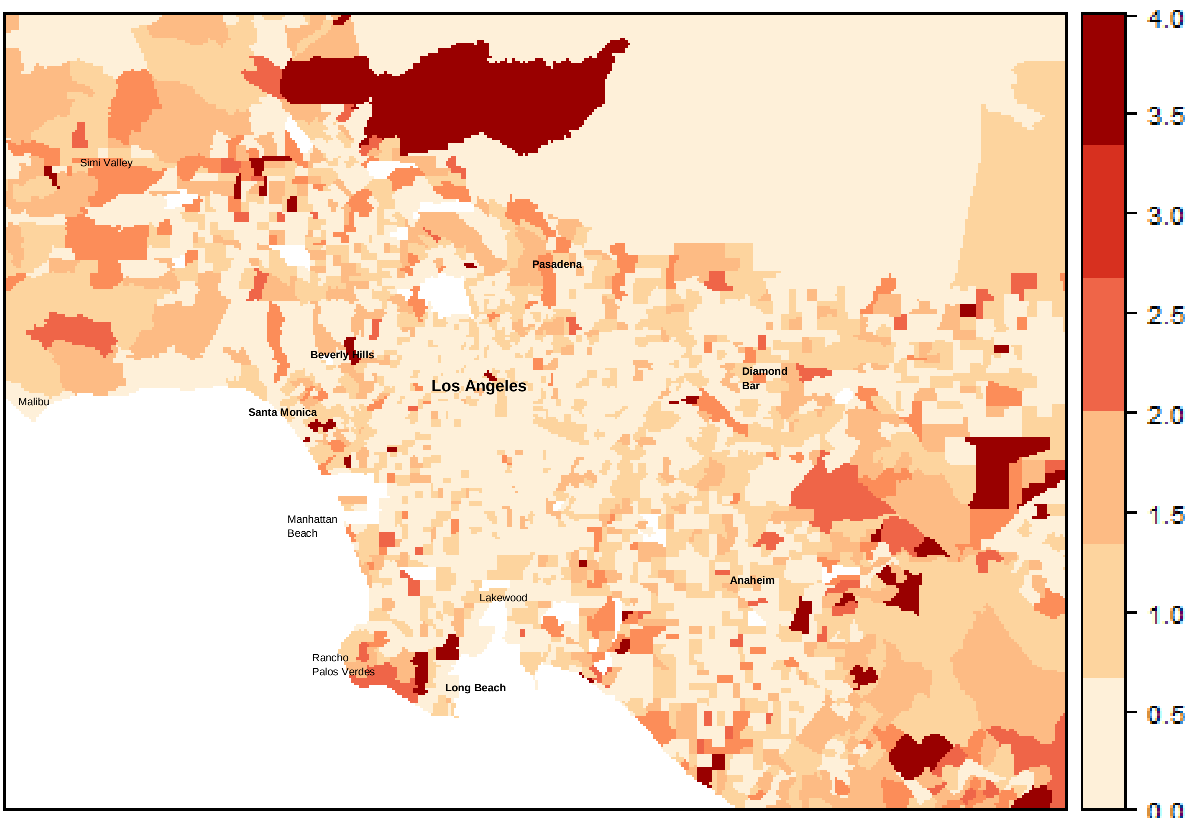
Figures 4-1, 4-2 and 4-3 show that purchases of used PEVs are much more evenly distributed across geographical space than new purchases. Although purchases are still clustered along the coast, the number of census tracts with high levels of purchases outside the Los Angeles and Bay Area Regions has increased dramatically. Further, within both Los Angeles and the Bay Area, we can see that major purchasers of used PEVs are more geographically dispersed and less-concentrated in high-income areas than purchasers of new PEVs. These results suggest that as the PEV market matures, we can expect PEV owners to become socioeconomically more diverse and the number of census tracts demanding access to electric charging stations to increase.

Figure 4-1: Used PEVs/1000 Households in California



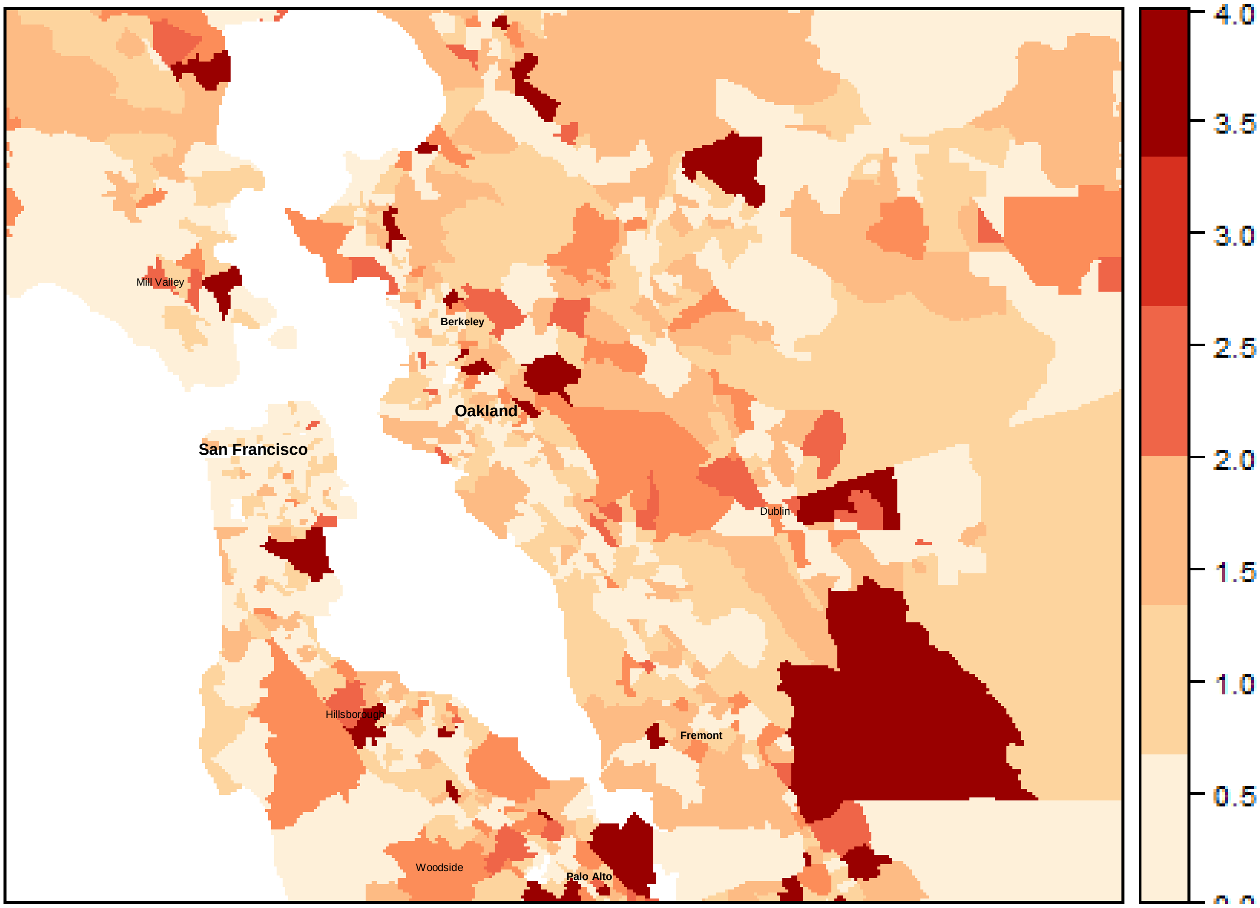
Source: IHS 2010-2015

Figure 4-2: Used PEVs/1000 Household in Los Angeles



Source: IHS 2010-2015

Figure 4-3: Used PEVs/1000 Households in Bay Area



Source: IHS 2010-2015

We next compare the characteristics of tracts by quartile of used PEV sales per household in Table 4-6. Similar to our analysis presented in section 4.2, we see that tracts in the highest quartile of used PEV ownership are higher income and more educated than tracts in lower quartiles. However, the difference is much less dramatic than in section 4.2, providing further evidence for what we saw visually in Figures 4-1,4-2, and 4-3: purchases of used PEVs are much less geographically concentrated than purchases of new PEVs. It is also important to note that the percentage of single family homes and length of HOV lane mileage remains much higher in tracts in the highest quartile of used PEV purchasing relative to other tracts; this is suggestive evidence of the importance of these two characteristics for both new and used PEV purchasers.

Table 4-6: Characteristics of Tracts by Quartile of Used PEV Sales per capita

	1st Quartile	**2nd Quartile**	**3rd Quartile**	**4th Quartile**
Tract Income Characteristics:				
Median Home Value	333,701	436,355	444,437	522,180
Homes Worth > $1 Mil	0.041	0.075	0.074	0.106
Income Over $200K	0.039	0.07	0.072	0.108
Tract Demographic Characteristics:				
Adults with Grad Degree	0.075	0.134	0.121	0.149
Workers in Mgmt, Info or Finance	0.104	0.142	0.136	0.149
White	0.612	0.69	0.64	0.652
Tract Commute Characteristics				
>40 Min Commute	0.199	0.2	0.206	0.221
Population Density (population/sq. mile)	9423.458	8036.919	8411.439	6242.145
Vehicles Per Household	1.815	1.814	1.9	2.05
Other Characteristics:				
Vote for AB32 Repeal	0.387	0.395	0.376	0.367
Single Unit Homes	0.733	0.67	0.704	0.8
HOV Miles in 5 Mi Radius	7.124	5.482	8.64	10.07

Source: American Community Survey 2013-2015; IHS 2010-2015

Finally, we created a predictive model which estimates used PEV sales per 1,000 households by census tract, similar to Table 4.1. Table 4-7 shows the results. There are two important takeaways from this model. First, unlike the PEV models in 4.3 and 4.4, we are unable to explain much of the variance in used PEV vehicle sales. Looking at the R-squared with our preferred specification, the model explains less than 20% of total variance. This again indicates the lack of geographic concentration in used PEV sales.

Second, the best predictors of used PEV purchases are very similar to the best predictors of new PEV purchases, but their predictive power is greatly reduced. This suggests that the factors associated with new PEV purchases still matter for used PEV purchases, but their effect is lessened because other, unobservable factors play a larger role in influencing purchase decisions.

Table 4-7: Abbreviated Regression Models Predicting Used PEV Purchases per capita

VARIABLES	(1) Used PEV/1000 HH	(2) Used PEV/1000 HH	(3) Used PEV/1000 HH	(4) Used PEV/1000 HH
Percent Income $150-$200k	0.322***	0.156***	0.113***	0.0840***
	(0.0109)	(0.0160)	(0.0182)	(0.0185)
Percent Income Over $200k		0.143***	0.134***	0.128***
		(0.0168)	(0.0188)	(0.0239)
Median Rent		0.120***	0.0878***	0.0738***
		(0.0150)	(0.0166)	(0.0172)
Percent w/ Income $125-$150k			0.0754***	0.0591**
			(0.0225)	(0.0237)
Earn >$75k and Commute Alone			0.0355*	0.0314*
			(0.0181)	(0.0181)
Percent in Poverty				-0.0380***
				(0.0127)
Median Home Value				0.0107
				(0.0197)
Percent Homes Valued $500-$750k				0.0502***
				(0.0138)
Constant	0.652***	0.652***	0.652***	0.652***
	(0.00943)	(0.00925)	(0.00922)	(0.00920)
Observations	7,855	7,855	7,855	7,855
R-squared	0.129	0.163	0.168	0.172

Source: American Community Survey 2013-2015; IHS 2010-2015

Standard errors in parentheses ***p<0.01, **P<0.05, *p<0.1

4.7 Summary of Model Results

PEVs are a growing part of the California light-duty vehicle fleet. However, new purchases of PEVs are concentrated in California's more affluent census tracts; the correlation between the percent of a tract's households earning over $200,000 and its PEV purchases/1,000 households is .82. Additionally, even after accounting for past trends in PEV purchases, higher-income tracts were more likely to purchase PEVs, indicating that PEV growth may be faster in higher-income tracts. These findings suggest that in 2015, new PEV ownership remains largely spatially concentrated among those with high SES status. Our analysis shows that this pattern is especially true for BEVs relative to PHEVs.

Yet, when we look at used PEV purchases a different picture emerges. Although this market remains small, used PEV purchasers come from much more socio-economically diverse census tracts suggesting that actual or perceived PEV price may be one of the largest barriers preventing new PEV take-up. Used PEV purchasers still live in tracts that have many more single-family homes and access to HOV lanes suggesting the continued importance of these attributes in PEV purchase decisions.

4.9 Conclusion

PEV purchases have grown rapidly in California over the past five years, reaching 3% of all new vehicle sales by 2014. In the Bay Area, PEV monthly sales have nearly reached parity with HEVs and in the state's other metropolitan areas PEV monthly sales are equal to half of HEV monthly sales. PEV sales have been concentrated in the state's largest metropolitan areas and in its wealthiest census tracts. The gap between these heavy purchasers of PEVs and the rest of the state has grown over time.

Chapter 5: Vehicle Rebate Uptake and the Effects of New Vehicle Introductions on Sales

5.1 Introduction

We address two distinct questions in this chapter. The first part of the chapter explores how vehicle rebate uptake varies across plug-in electric vehicles (PEV), battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV) and vehicle brands, as well as over time. Consumers who purchase or lease PEVs are eligible to receive a clean vehicle rebate of $1,500 for PHEVs and $2,500 for BEVs in California. Preliminary analysis suggests that not everyone who is eligible for the rebate actually applies for the rebate. Low uptake rates may signal a lack of policy awareness on the part of both dealerships and buyers, which if remedied, may lead to higher PEV sales. We also explore what explains differences in neighborhoods' vehicle rebate uptake.

The second part of this chapter explores whether the introduction of new PEV models increased aggregate PEVs sales. One of the goals of California's zero-emission vehicle (ZEV) mandate policy is to increase the production of PEVs with the hope that providing a greater choice of PEVs will lead to greater PEV sales. Here we evaluate how the introduction of PEV models over the course of the market has affected PEVs sales. More specifically, we explore the role that model loyalty may play by comparing the sales of PEV versions of pre-existing models; such as the Ford Fusion or Toyota Prius, to sales of PEVs not linked by name to pre-existing models. We also evaluate how the introduction of sequential models into a body-type class affects PEVs.

5.2 Rebate Uptake Across California

The state of California offers generous rebates to purchasers and lessors of PEVs. However, through October 2015, more than one-fourth of eligible consumers did not apply for a rebate. In this section, we document rebate uptake rates across different subgroups in the population and describe factors that may be driving these differences. Figure 5-1 shows the percentage of PEVs purchased by a given date whose owners had applied for a tax rebate. We can see that although the rate has risen slowly over time, for the past three years it has remained largely flat around 70%.

Figure 5-1: PEV Rebate Uptake

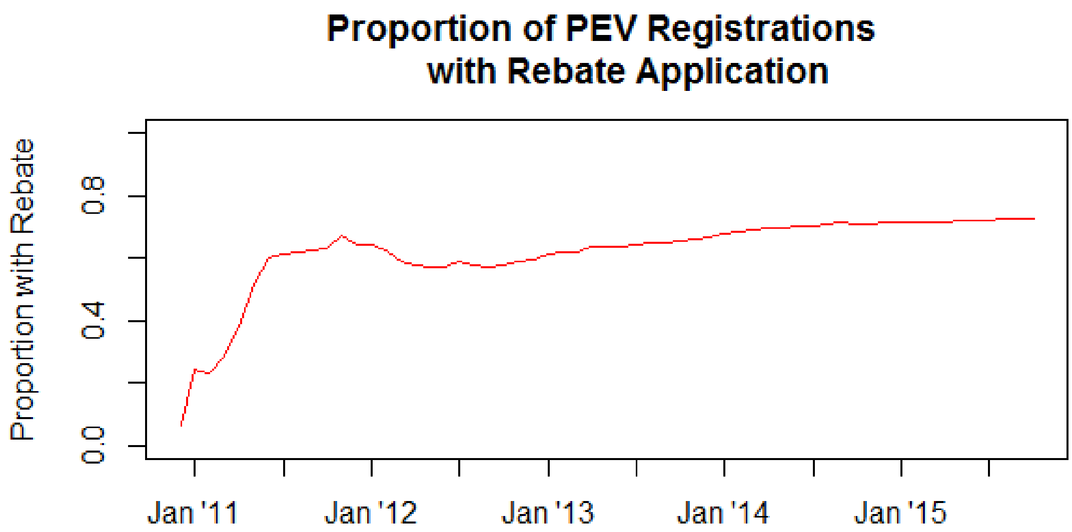
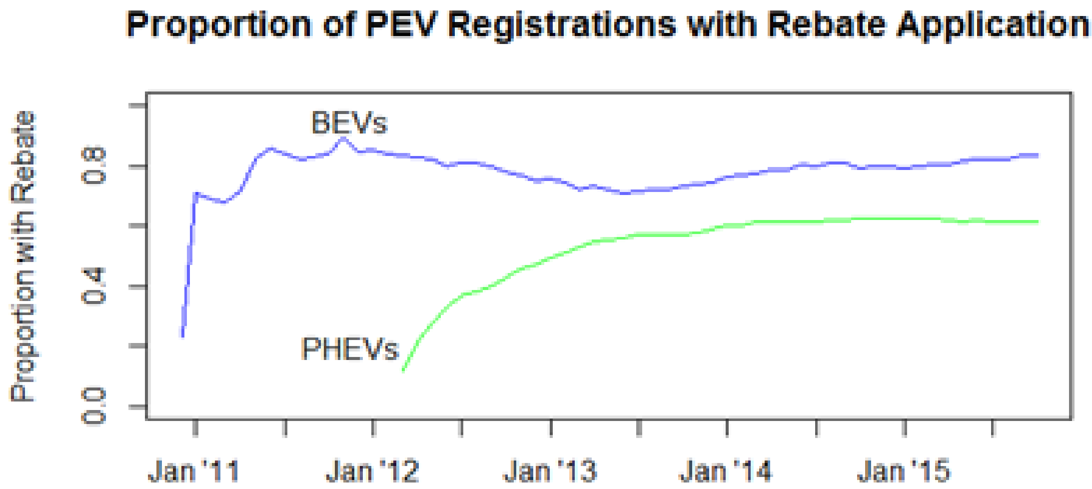
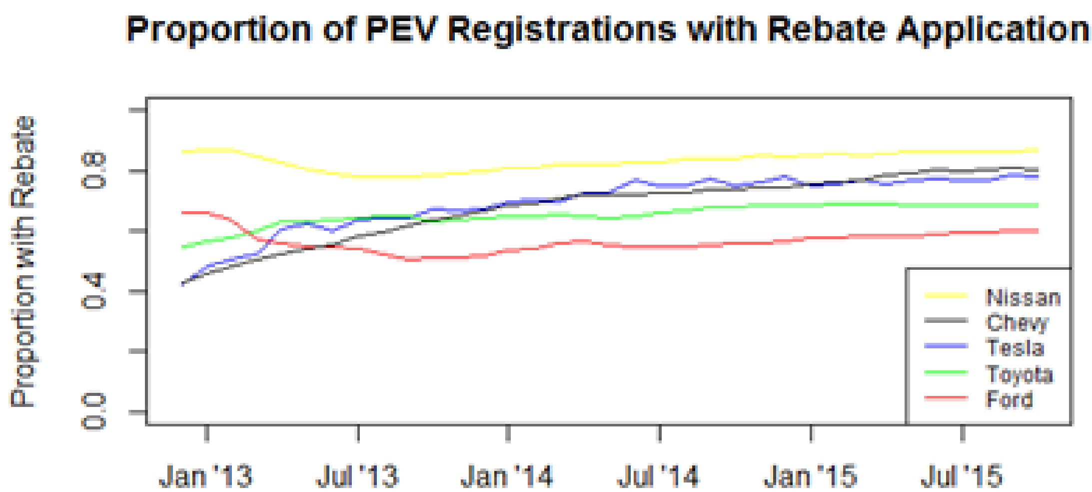


Figure 5-2 shows rebate uptake broken down by drivetrain and brand (vehicle “make”). In general, BEV owners have higher rebate-uptake rates. Rates are particularly high for Nissan owners and low for Ford owners.

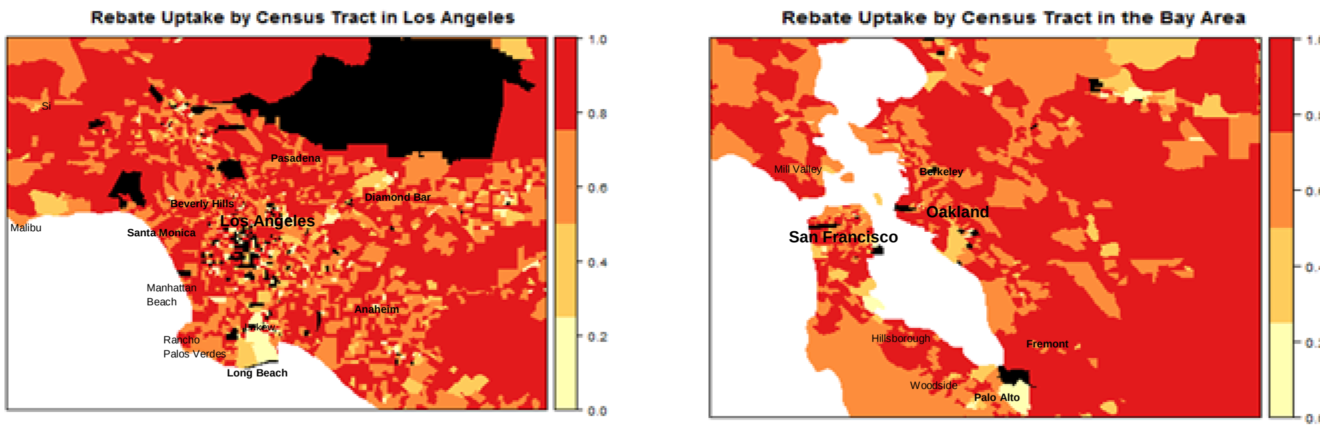
Figure 5-2: PEV Rebate Uptake by Subgroup





We next map rebate-uptake rates by census tract in Los Angeles and the Bay Area. Areas in black have no PEV registrations. We find that there appears to be little spatial correlation in PEV rebate uptake. It does seem that more densely populated areas (downtown LA and San Francisco) are less likely to apply for the PEV rebate, but this relationship is not very strong.

Figure 5-3: Map of Rebate Uptake by Percentage



Finally, we again use a LASSO regression to identify the best predictors for rebate uptake within a given census tract. Tables 5-1 and 5-2 show the results. Rebate Tables 5-1 and 5-2 include Model Fixed Effects (rebate percentage is a cumulative measure so we could not include time effects). Table 5-1 is all PEVs and Table 5-2 includes only tracts which have purchased ten or more PEVs.

Table 5-1 Factors Correlated with the Percentage of Rebates Issued

VARIABLES	(1) % Rebate	(2) % Rebate	(3) % Rebate	(4) % Rebate	(5) % Rebate
Prop. Income > $100k	0.235***	0.166***	0.147***	0.131***	0.142***
	(0.0312)	(0.0320)	(0.0322)	(0.0329)	(0.0332)
Prop. Home < $150k		-0.155***	-0.137***	-0.109**	-0.137**
		(0.0424)	(0.0426)	(0.0444)	(0.0546)
Prop. Asian			0.125***	0.105***	0.142***
			(0.0231)	(0.0244)	(0.0268)
Prop. Employed				0.112*	0.135**
				(0.0627)	(0.0649)
Prop. Com. <10 min				-0.179**	-0.151**
				(0.0762)	(0.0769)
Pct. PEV Fords	0.0896**	0.0887**	0.0982**	0.0956**	0.0748*
	(0.0389)	(0.0387)	(0.0390)	(0.0392)	(0.0395)
Pct. PEV Teslas	0.0246	0.0307	0.0506	0.0659	0.0549
	(0.166)	(0.166)	(0.166)	(0.167)	(0.159)
Pct. PEV Chevy	-0.0932**	-0.0896**	-0.0743*	-0.0688	-0.0625
	(0.0440)	(0.0440)	(0.0445)	(0.0445)	(0.0452)
Pct. PEV Nissan	0.112**	0.115**	0.116**	0.117***	0.111**
	(0.0453)	(0.0456)	(0.0455)	(0.0453)	(0.0456)
Pct. PEV Toyota	-0.152**	-0.153***	-0.153***	-0.152***	-0.155***
	(0.0594)	(0.0591)	(0.0592)	(0.0591)	(0.0596)
Constant	0.698***	0.736***	0.718***	0.676***	0.675***
	(0.0165)	(0.0176)	(0.0184)	(0.0418)	(0.0464)
County Fixed Effects[18]	N	N	N	N	Y
Observations	7,307	7,307	7,307	7,307	7,307
R-squared	0.020	0.023	0.025	0.027	0.051

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[18] A county fixed effects model is a time-series panel model that controls for unobserved county-level variables thus ensuring that they do not confound the estimated relationships of interest.

Table 5-2 Rebate Factors correlated with the Proportion of Rebate Uptake for Tracts that purchased 10 or more PEVs

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Prop. Rebate	Prop. Rebate	Prop. Rebate	Prop. Rebate	Prop. Rebate
Prop. Income > $100k	0.270***	0.225***	0.207***	0.184***	0.199***
	(0.0230)	(0.0243)	(0.0241)	(0.0245)	(0.0260)
Prop. Home < $150k		-0.248***	-0.217***	-0.184***	-0.170***
		(0.0575)	(0.0565)	(0.0569)	(0.0581)
Prop. Asian			0.167***	0.152***	0.160***
			(0.0193)	(0.0198)	(0.0212)
Prop. Employed				0.172***	0.183***
				(0.0415)	(0.0420)
Prop. Commute <10 min				-0.167***	-0.134**
				(0.0567)	(0.0625)
Pct. PEV Ford	0.167***	0.157***	0.218***	0.205***	0.156***
	(0.0389)	(0.0389)	(0.0395)	(0.0396)	(0.0402)
Pct. PEV Tesla	-0.345***	-0.336***	-0.241***	-0.205***	-0.189***
	(0.0666)	(0.0664)	(0.0667)	(0.0670)	(0.0690)
Pct. PEV Chevy	-0.115**	-0.115**	-0.0384	-0.0345	-0.0251
	(0.0455)	(0.0451)	(0.0460)	(0.0457)	(0.0479)
Pct. PEV Nissan	0.264***	0.269***	0.284***	0.279***	0.225***
	(0.0589)	(0.0577)	(0.0576)	(0.0574)	(0.0622)
Pct. PEV Toyota	-0.0909*	-0.0958*	-0.100*	-0.0946*	-0.0718
	(0.0532)	(0.0527)	(0.0519)	(0.0518)	(0.0557)
Constant	0.653***	0.684***	0.637***	0.559***	0.580***
	(0.0168)	(0.0180)	(0.0190)	(0.0319)	(0.0367)
County Fixed Effects	N	N	N	N	Y
Observations	4,029	4,029	4,029	4,029	4,029
R-squared	0.066	0.074	0.092	0.099	0.142
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

Table 5-1 shows the results with all census tracts and Table 5-2 just with tracts with ten or more PEV registrations. None of our models do a very good job of predicting rebate-uptake, suggesting that uptake may be determined by factors outside our model such as whether an individual chooses to buy or lease a vehicle, dealership knowledge or other unobserved factors. In general, higher income is associated with rebate uptake, with a ten percentage-point increase in the amount of household earning over $100,000 associated with a 1.3 percentage-point increase in rebate applications. A symmetric, but negative association holds for the percentage of census tract homes worth less than $150,000.

The results of this analysis suggest more research is needed to determine what drives differential rebate uptake. Given the differences across models seen in Table 5-1 and 5-2, one might hypothesize that dealership characteristics play an important role, but more data is needed to test this hypothesis.

5.3 New Model Introduction Impacts on PEV Sales

Automakers' introduction of new PEV models should expand consumers' choice set which may, in turn, increase new PEV sales. The addition of a new PEV model may have several effects on consumer choice. First, such introductions may expand new body types, vehicle classes, and brands available as PEVs. Second, the cumulative introduction of PEVs within a vehicle body type may signal to consumers that PEVs have become a more proven and reliable option.

The size of the effects on PEV sales of particular PEV model introductions also depends upon the characteristics of that vehicle or consumer segment. For example, one might hypothesize that the introduction of a first PEV model into a popular body type (e.g., midsize sedan) will have a larger effect on sales than an introduction into a smaller segment (e.g., convertibles). Similarly, we might expect that when a PEV model of a popular existing model (e.g., Ford Fusion) is introduced it will spur short-run sales more than the introduction of models with which consumers are wholly unfamiliar (e.g., CODA's).

Of course some new PEV models may prove to be popular over the long run, such as Tesla's Model S or Chevy's Volt. Finally, the introduction of a new PEV model could take market share away from PEV models in the same vehicle segment that were introduced earlier. Conversely, the addition of the new PEV model may boost sales of subsequently introduced models if consumers view the introduction as a sign the technology is maturing.

In this section we evaluate the effects of automaker's introduction of specific PEV models on total PEV market sales. Our general empirical strategy is to evaluate whether the introduction of a specific PEV model is correlated with a significant increase in future cumulative sales. We are able to include in our analysis all PEVs introduced to the California market from December 2010 to June 2014. To evaluate the hypotheses discussed above we estimate several different models that characterize new model introductions in several ways. However, as we discuss further below, an important limitation of our modeling approach is the omission of several variables on the new and used conventional internal combustion engine (ICE) vehicles sold over this same period.

5.4 Summary of Findings

The progressive introduction of increasing numbers of new PEV models does appear to, in general, increase total future PEV sales. Several of our model specifications effectively evaluate our preliminary hypotheses. First, PEV versions of pre-existing models exhibit much higher future sales compared to brand new PEV models. For example, PEV sales associated with models such as Fusion, SMART, Prius, and SOUL were significantly higher than completely new PEV models.

Second, the introduction of a second PEV model of a given body type had a bigger impact on sales than third and fourth PEV introductions, which were also positive and statistically significant. This suggests that some consumers may interpret the expansion of PEV models within a vehicle segment as a sign that the vehicle is maturing, becoming more reliable and proven. Interestingly, the coefficient on the first model introduced was not significant, perhaps because this early market did not have much of a clear trend.

Our efforts to model the effects of very specific model introductions is limited by our inability to control for important omitted variables associated with conventional new ICE prices and sales. We discuss below how these omitted variables could significantly bias our estimated results. Therefore, we view these estimated results with skepticism and do not report them here.

5.5 Methods, Data and Limitations

We have data on the introduction of all PEV models in California by month from December 2010 to June 2014. These models are presented in Table 5-3 and discussed below in Section 5.6.1.

Given the available data, our approach is to regress PEV sales growth on variables that characterize, in various ways, the introduction of new PEV models. Intuitively, these correlations measure how much future aggregate PEV sales have increased as a result of early model introductions.

A significant limitation of our approach is that we cannot control for the price, body type, vehicle class or brand of ICE vehicles offered in the market over a relevant time. This is important because these ICE vehicles are the substitutes that consumers face. Changes in their price, quality, and general availability will affect sales of PEVs.

Consider, for example, a market scenario in which a new PEV model was introduced in the same month that an automaker i) lowered an ICE's price, ii) introduced a new type of ICE, or iii) offered a new attractive financing program. In this case, consumers may increase their purchase of ICEs into the future, decreasing the relative sales of PEVs. If we fail to control for these omitted variables we might find that the introduction of a PEV model is negatively correlated with future PEVs as consumers increase their purchases of ICEs and reduce their relative purchases of PEVs. But we would be mistaken to interpret that negative correlation as the PEV introduction causing a decline in future PEV sales. Rather that decline was potentially caused by ICE becoming more attractive, causing consumers to substitute toward ICEs and away from PEVs. If we were able to control for the effects of changes in the ICE market within our model, we would more accurately and validly measure the correlations between the PEV model introduction and future PEV sales.

With this data limitation in mind, we are able to perform some analysis which relies upon more aggregated measures of PEV model introductions. For example, we aggregate by whether the introduced PEV had a pre-existing ICE model or whether it was an entirely new PEV model. We also aggregate by the rank order the PEV model was introduced. The sign and magnitude of these more aggregated measures are less likely to be impacted by omitted ICE variables.

5.6 Results

5.6.1 Sales by PEV Model

Table 5-3 provides PEV sales between 2010 and 2014 by release year and model for California. During this time period, almost 120,000 PEVs in over 28 models were sold in California. In recent years, the number of new models released each year has remained fairly constant. Based on automakers announcements, this rate is expected to continue through 2016. While over half of these models are hatchbacks or smaller coups, larger sedans, coups and SUVs have also been introduced and are beginning to infiltrate these product niches. Several traditional luxury brands have also entered the PEV market, especially in 2014.

Despite the large number of models listed in Table 5-3, most of the volume in this market is concentrated in a few models. The final column of the table provides a top 10 ranking by sales. Early entrants in 2010, including the Chevrolet Volt (rank 1st), Nissan LEAF (2nd), and the Tesla Model S (4th), lead the market in total sales. PEV versions of pre-established models comprise the remaining models found in the top 10.

Table 5-3: Sales of PEV Models Released by Year and Body in California Through 2014

Release Year	Model	Body	Sales*	Top 10 Ranking
2010	TESLA ROADSTER	Luxury Coupe	156	
	NISSAN LEAF	Hatchback	25,206	2
	INTERNATIONAL ESTAR	Van	37	
	CHEVROLET VOLT	Hatchback	26,197	1
2011	SMARTCAR FORTWO	Coupe	2,122	9
	AZURE TRANSIT CONNECT	Van	59	
	MITSUBISHI I-MIEV	Hatchback	255	
2012	BMW ACTIVE E	Luxury Coupe	457	
	FORD FOCUS	Hatchback	1,209	
	TESLA MODEL S	Luxury Hatchback	15,521	4
	HONDA FIT	Hatchback	92	
	TOYOTA RAV4 EV	SUV	2,221	8
	FISKER KARMA	Luxury Sedan	270	
	TOYOTA PRIUS PLUG-IN	Hatchback	18,163	3
2013	CHEVROLET SPARK	Hatchback	1,338	10
	FIAT 500	Hatchback	7,736	6
	FORD C-MAX	Hatchback	6,002	7
	HONDA ACCORD	Sedan	589	
	FORD FUSION	Sedan	7,945	5
2014	BMW 13 BEV PLU	Hatchback	896	
	MERCEDES-BENZ B-CLASS BCL	Hatchback	565	
	KIA SOUL EV	SUV	286	
	CADILLAC ELR	Luxury Coupe	302	
	PORSCHE PANAMERA S HYB	Luxury Sedan	202	
	MCLAREN PI PLU	Luxury Coupe	15	
	BMW 13 REX HYB	Hatchback	1,040	
	PORSCHE 918 SPY PLU	Luxury Coupe	14	
	VOLKSWAGEN GOLF SPR PLU	Hatchback	219	

Source: IHS 2010-2015

5.6.2 Order Effects of Introduction by Body Type

The ICE vehicle market offers several dozen vehicle choices for each major body type. One might hypothesize that as PEV models are introduced within each vehicle body type, the initial effect would be an increase in cumulative PEV sales as the number of PEV models with each body type grows. For example, within mid-size sedans or hatchbacks, as the number of PEV models expand across brands we would expect sales of PEV mid-size sedans or hatchbacks to grow respectively.

In the foregoing model, we regress total PEV sales on indicator variables for when a new introduction is the first model, second model, third, and so on within each major body type. This model, shown in Table 5-4, is based on sales at the census tract level by month. We find that the first introduction is positive but not statistically significant. In addition, the coefficient is relatively smaller than for the other higher-order introduction effects. This may be because consumers were simply not generally aware of the introduction of the very first model within a body type but as the number of models increases they focus more on PEVs as a serious purchase opportunity.

For the higher order introductions we do find positive and very significant effects. In particular, the second model of a body type introduced has a much larger (0.112), statistically significant effect than subsequent introductions. This suggests that for the major body types that we examine, having two PEV models available raises awareness and future sales considerably. The effects of the higher-order introductions are a quarter (0.025) to a tenth (0.009) the size of the second introduction. This suggests modest and positive increases in sales as future brands introduce PEV models to each body type.

Table 5-4: The Order Effects of PEV Model Introduction by Body Type

reg_pev	**[95% Conf. Coef.**	**Std. Err.**	**z**	**$P > \lvert z \rvert$**	**Interval]**	
first_pev	0.003	0.003	0.94	0.346	-0.003	96557
second_pev	0.112	0.008	14.78	0	0.097	0.127
third_pev	0.010	0.005	1.84	0.066	-0.001	0.020
fourth_pev	0.026	0.011	2.41	0.016	0.005	0.047
fifth_andmore_pev	0.026	0.001	21.71	0	0.024	0.029

5.6.3 Effects of Introducing PEV Versions of Pre-existing ICE Models

One might hypothesize that the introduction of a PEV version of a pre-existing ICE model would experience higher PEV sales compared to brand new PEV models. Consumers who have already revealed they are attracted to an ICE model, and trust that brand, are likely to feel relatively less risk in purchasing a PEV of that type as compared to a new model from a possibly new brand.

Reviewing the PEVs introduced in Table 5-3, we identify the following PEV models have an equivalent ICE version: Smart Car, Ford Focus, Honda Fit, Toyota Rav4, Chevy Spark, Fiat 500, Mercedes B-Class, Kia Soul, Toyota Prius, Ford C-max, Honda Accord, Ford Fusion, Porsche Panamera, Porsche 918, and VW Golf. We will categorize the remaining models in the table as new.

We regress future cumulative PEV sales on an indicator variable for the introduction of a pre-existing or non-pre-existing ICE model. We present the results in Table 5-5. The results suggest that PEV models associated with pre-existing ICE models have positive and significant higher correlations with future cumulative sales than does the introduction of completely new PEV models. We do this analysis at the census-tract level, but find a similar significant result at the county level.

Table 5-5: Effects of Introducing PEV Versions of Pre-existing ICE Models

reg_pev	Coef.	Std. Err.	Z	P > |z|	[95% Conf. Interval]
model_exist	0.389721	0.0014792	26.35	0.000	.0360729 0.0418712
model_non_exist	-0.0012013	0.0021024	-0.57	0.568	-0.0053219 0.0029194

5.6.4 Exploring Complementary and Substitution Effect of Across PEV Model Introductions

What effect does the introduction of one PEV model have on the future sales of other PEV models? Does one model take future market share away from the other model? Or might the introduction of one model actually increase sales of other PEV models? This complementary relationship might be more likely to exist if each of two models being considered is of a different body type or brand. In this case, the introduction of one PEV might reassure the prospective consumers of the other PEV model that PEV technology in general is here to stay, is reliable, and also desirable. In other words, knowledge spillover between models could create early market complementarities. Theoretically, models could be either substitutes or complements or both over time. To answer these questions would require empirical analysis.

We empirically explore relationships among PEVs with significant sales over our period of study and target similar consumer segments for the state of California. Specifically we investigated the impacts of the introduction of the Fortwo electric, Prius Plug-in, and Fusion Energi on LEAF and Volt future sales. In three different models, we regressed the registrations of the LEAF and Volt on an indicator for introduction of the Smart Car, Prius and Fusion. These results are presented in Table 5-6.

Somewhat surprisingly, it appears that the introduction of popular but slightly different PEV body types increases the future sales of the other PEV model examined in each regression. The size of the effects are small (compared to previously presented results) but highly significant. While in a mature market we might expect the models to be substitutes for each other, competing for market share, during this early phase of the market they appear to have, on net, a complementary relationship.

Table 5-6: Assessing Complementary and Substitution Effect of Across PEV Model Introductions

reg_leaf	**Coef.**	**Std. Err.**	**Z**	**P > |z|**	**[95% Conf. Interval]**
ind_smart	0.101535 0.0012248	82.90	0.000	0.0991344	0.1039357

reg_volt	**Coef.**	**Std. Err.**	**Z**	**P > |z|**	**[95% Conf. Interval]**
ind_prius	0.037004 0.0033672	82.90	0.000	0.0991344	0.1039357

reg_volt	**Coef**	**Std. Err**	**Z**	**P > |z|**	**[95% Conf. Interval]**
ind_fusion	0.0192518	0.0024532	7.85	0.0144437	0.02406

5.7 Summary of Findings for New Vehicle Introductions

California's ZEV regulation was designed with the intention to increase PEV sales among new vehicles. In particular, the regulation assumes that as new PEV models are introduced into the market, consumers will be more likely to purchase PEVs. In this chapter we evaluated the effects of automaker's introduction of specific PEV models on total PEV market sales.

Our analysis brings to light the following. First, PEV versions of a pre-existing model exhibit much higher future sales compared to previously unknown PEV models, suggesting that model loyalty by consumers played an important role in demand for some vehicle sub-segments. Second, the introduction of a second model of a certain body type had a bigger impact on sales than third and fourth introductions. Third, we find some model introductions to have a complementary (or additive) impact on sales of other PEV models.

Unfortunately, our results are limited by the omission of several variables on the new and used conventional internal combustion vehicles sold over the same time period that we analyze. We are unable to control for these important omitted variables therefore potentially biasing our estimated results.

Chapter 6: How does the Presence of HOV Lanes Affect Plug-in Electric Vehicle Adoption in California? A Generalized Propensity Score Approach

6.1 Introduction

Policymakers commonly design policies with the goal of increasing consumers' adoption of newer, less- polluting technologies, including clean vehicles.[19] A common policy approach has been to grant drivers of these clean vehicles access to high occupancy vehicle (HOV) lanes in an effort to increase the utility or value that drivers derive from the use of these vehicles.[20] Historically, nine states adopted such policies for hybrid vehicles. More than a dozen states have similar policies for plug-in electric (PEV) and natural gas vehicles, with more states likely to offer future policies for hydrogen fuel cell vehicles (DeShazo et al., 2015).

In this chapter we identify the causal impacts of these policies on the adoption of PEVs in California between 2010 and 2013. Complicating the evaluation of this policy is the fact that high-occupancy vehicle (HOV) lanes are geographically distributed highly unevenly throughout the state of California, as are prospective new car buyers who might adopt these vehicles. Researchers have shown that the average clean vehicle owner is willing to pay a premium for access to HOV lanes in the case of both hybrid vehicles (Shewmake and Jarvis, 2014) and PEVs (DeShazo, Sheldon, and Carson, 2015). In light of this it is somewhat puzzling that several correlational studies have shown a weak relationship between hybrid sales and HOV lane access (Diamond, 2008; Gallagher, Sims, and Muehlegger, 2011). What has been missing in this literature, and what we estimate for PEVs, is the causal relationship between variation in geographic access to the HOV lane miles and geographic sales of clean vehicles.

We would like to measure the value of HOV access to current and prospective PEV drivers. Ideally we would know how many HOV lane miles each driver could utilize if they had access to these lanes because they owned a PEV. The data that we have available to use for analysis in this chapter does not allow us to know or measure this. Instead, we will use a household's access to HOV lane miles as a measure of the size of the potential benefits. (In the next chapter, where we analyze household survey data, we know whether households use HOV lanes.)

[19] Other types of incentives in place to encourage PEV adoption include a federal tax credit program, the California Clean Vehicle Rebate Project, reduced electricity rates for PEVs and publicly subsidized refueling infrastructure.

[20] For a discussion of the social costs of these policies see Bento et al. (2014) and Shewmake and Jarvis (2014).

Methodologically, we use a generalized propensity score matching approach to estimate the impact of HOV lanes on PEV sales, controlling for the probability of treatment (HOV lane density). Standard propensity score matches conditions on a binary variable, e.g., whether or not a census tract is near HOV lanes. However, we are interested in a continuous conditioning variable, namely, how many miles of HOV lanes a census tract is near. First, we estimate a generalized propensity score (GPS) for each census tract, which tells us how many miles of HOV lanes are likely to be within a given radius of a tract based on a large set of covariates such as income, race, age, education, political views, and commuting patterns. Then, controlling for propensity score, we estimate a dose-response function, which tells us how PEV sales change as the number of nearby HOV lanes increases. PEVs, which include battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), have been gaining traction in the California market in recent years. We evaluate effects of HOV lanes on both BEV and PHEV sales, separately and together.

In California, PEVs have free single-occupant access to HOV lanes through 2019. An unlimited number of white decals are available that allow BEVs access to HOV lanes. PHEVs are granted HOV access via green decals. Originally, green decals were to be allocated to the first 40,000 applicants who purchased a "transitional zero emissions vehicle," which are PHEVs. In mid-2014 the green decal limit was increased to 55,000 and has subsequently been increased to 85,000. As of December 31, 2013, the end of our analysis period, 28,739 green decals had been issued and as such the decal cap was not binding.[21]

6.2 Theoretical Model

Consumers can purchase a private good, a PEV, for a premium over a conventional vehicle to gain access to a certain quantity and quality of HOV lanes.[22] Let the price of a conventional, internal combustion engine (ICE) vehicle be p_{ice}. Suppose there exists a PEV that is otherwise identical to the ICE vehicle. The PEV can be purchased for a premium of α over the ICE vehicle price, i.e., $p_{pev} = p_{ice} + \alpha$. Consumer i will purchase the PEV if the utility from the PEV is greater than the utility from the ICE vehicle that she is otherwise planning to purchase, i.e., if $u_{pev} > u_{ice}$.

Suppose a social planner has the ability to create q miles of HOV lanes of quality l at cost $c(q, l)$ to which PEVs have free single-occupancy access. We can think of quality as a measure of desirability of HOV lane placement, congestion, and other factors that may influence consumer utility derived from driving in a given HOV lane. The social planner seeks to maximize the utility to consumers of purchasing PEVs, subject to a budget B:

[21] Details can be found at http://www.arb.ca.gov/msprog/carpool/carpool.htm.
[22] This model does not preclude households from carpooling as well.

Equation 6-1

$$max_{\{q,l\}} \sum_i u_{i,PEV}$$

Equation 6-2

$$S.T.\, c(w,l) \leq B$$

The utility to consumer i of purchasing the ICE vehicle is her ex ante utility for the vehicle minus the price of the vehicle, $u_{i,ice} = v_i - p$. The utility to consumer i of purchasing the PEV is her ex ante utility for the vehicle, minus the price of the vehicle, plus her utility from HOV lane access, $f_i(q,l)$, plus some value w, which represents the consumer's preference for the PEV relative to the ICE vehicle. For example, w_i may be positive if the consumer derives utility from knowing that she is contributing less to air pollution and increased fuel savings, or w_i may be negative if the consumer is averse to behavioral changes such as plugging the vehicle in to charge. Therefore,$u_{i,pev} = v_i - p_{ice} - a + f_i(q,l) + w$. Equation 6-1 then becomes

Equation 6-3

$$max_{\{q,l\}} \sum_i v_i - p_{ice} - a + f_i(q,l) + w_i = max_{\{q,l\}} \sum_i f_i(q,l)$$

The Lagrangean of the constrained maximization problem is therefore

Equation 6-4

$$L = f_i(q,l) + \lambda[B - c(q,l)]$$

Simplifying the first order of conditions, we find

Equation 6-5

$$\frac{\frac{\partial f_i}{\partial q}}{\frac{\partial c}{\partial q}} = \frac{\frac{\partial f_i}{\partial l}}{\frac{\partial c}{\partial l}}$$

Equation 6-5 implies that at the optimal level of HOV lane provision, the ratio of the marginal benefit to marginal cost of the quantity of HOV lanes, is equal to the ratio of the marginal benefit to the marginal cost of the quality of HOV lanes. In our empirical section, we estimate a dose-response curve that tells us about the shape of $\frac{\partial f_i}{dq}$ over different ranges of q. Combined with knowledge on the marginal cost of HOV lane provision, policy makers might use this information to identify the optimal level of q.

6.3 Data

PEV registration data were purchased from IHS. The dataset lists PEV registrations by month and by census tract for California during February 2010 through December 2013. Each model is classified as a BEV, which has only an electric engine, or a PHEV, which has both an electric engine and an internal combustion engine. In this analysis we use cumulative PEV sales (including both BEV and PHEV) as of December 2013 as the dependent variable or outcome of interest.[23]

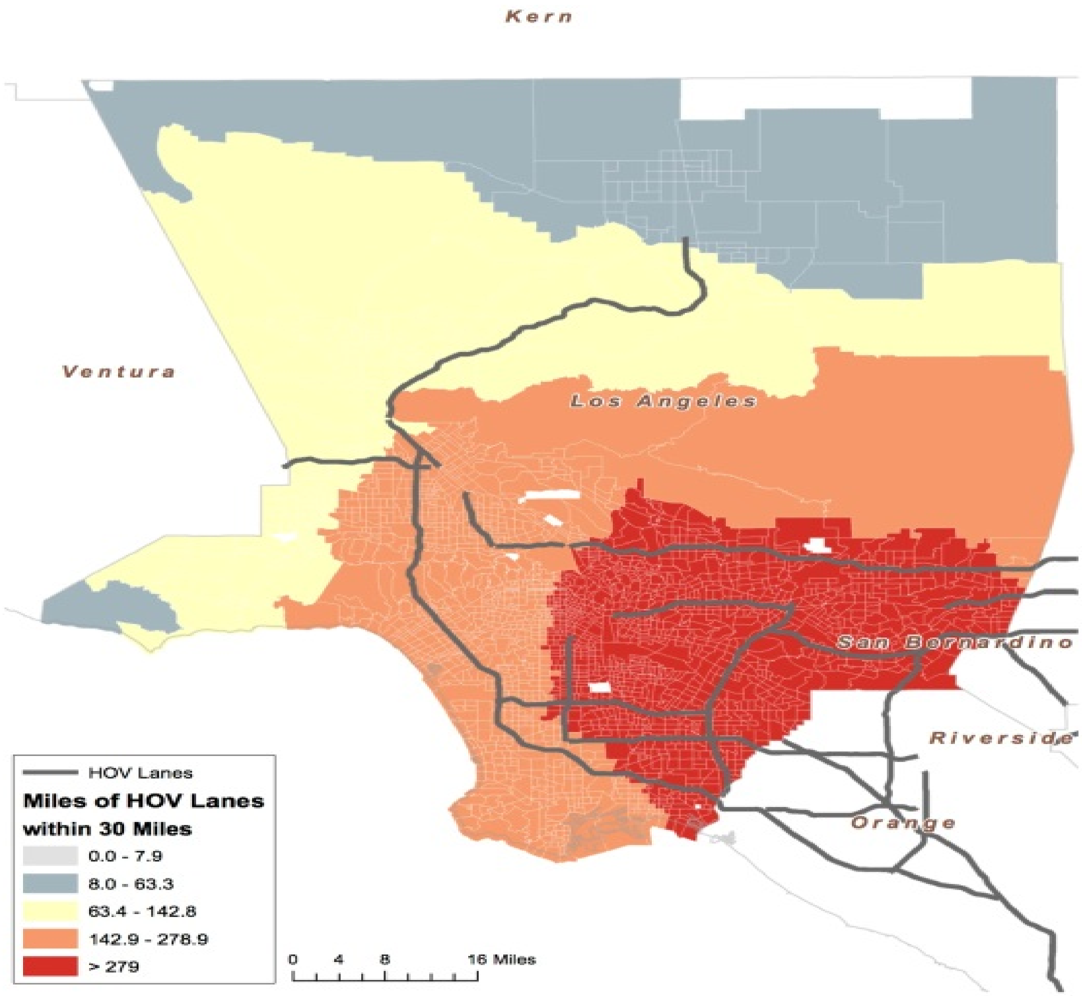
The treatment variable is the number of miles of HOV lanes ("lane-miles") within a 30-mile radius of the population centroid of a census tract as of December 2013.[24,25] The data on geographical locations of HOV lanes in California are collected by Caltrans and made public on the Caltrans website. Figure 6-1 shows HOV lane density and PEV registration density in the county of Los Angeles as an example. Figure 6-1a, below, shows that HOV lane density is highly correlated with urban areas.

[23] Our analysis implicitly assumes a uniform distribution of PEV supply at dealerships across California. While there may be heterogeneity in dealers' understanding and ability to educate prospective buyers, availability of vehicles across dealerships is likely uniform due to their ability to trade vehicles across dealerships. In other words, if a customer would like to purchase a PEV from a dealership that is out of stock, the dealership can transfer the PEV from another dealership.

[24] The average length of weekday home to work trips in California is 26 miles (Caltrans, 2013). A 30-mile radius is large enough to encapsulate most commuters' daily commutes but small enough to reflect variation across census tracts.

[25] While density of HOV lane-miles is not a perfect measure of HOV access, it is a good proxy for HOV lane access. HOV lane-mile density is highly correlated with being in an urban area, as is HOV lane access, i.e., the distance of a census tract from a highway entrance ramp with an HOV lane. Provision of these entrance ramps by Caltrans is generally in response to growing population density.

Figure 6-1a: HOV Lane Density in Los Angeles County

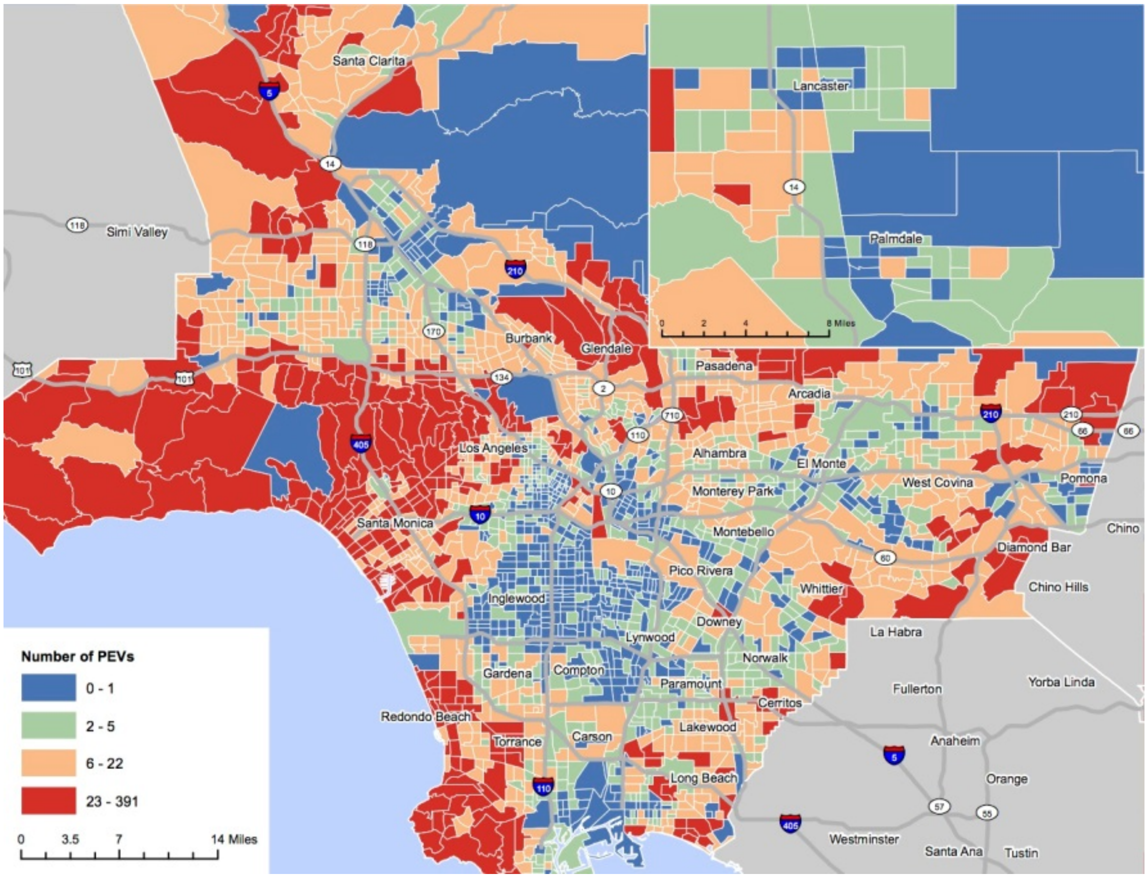


Source: GIS Independent Analysis

PEV density, as shown in Figure 6-1b below, appears to be relatively uncorrelated with HOV lanes.[26] (We have chosen density categories to highlight the spatial variability.) Instead, greater PEV density is found in more affluent and coastal areas. PEV-dense census tracts are found both in census tracts with high and low HOV lane densities.

[26] This supports the first key assumption from Section 6.3 that assignment of HOV lanes is independent of PEV sales.

Figure 6-1b: EV Registration Density in Los Angeles County



Source: IHS 2010-2015

Most of the covariates are socio-demographic variables (see Table 6-2) from the U.S. Census Bureau's 5-year 2008-2012 American Community Survey (ACS). We also use the share of a voting district voting "no" on California Proposition 23 as a measure of its green propensity. California Proposition 23 was a 2010 ballot measure to suspend AB 32, the "Global Warming Solutions Act of 2006." A higher proportion of "no" votes should correlate to a higher green propensity, and vice versa. Average gasoline prices for December 2013 by census tract were obtained from Gas Buddy Organization Inc. Average overnight electricity rates in December 2013 by census tract were obtained directly from utilities' rate schedules. Lastly, publicly-available PEV charger density (Level 1 Chargers, Level 2 Chargers, and DC Fast Chargers within a 5-mile radius of the population centroid of each census tract) as of December 2013 were obtained from the U.S. Department of Energy's Alternative Fuels Data Center. PEV charger density is a measure of the amenability of the built environment to PEV ownership.

Table 6-A.1 in the Appendix shows average covariate levels for census tracts in the bottom, middle, and top third of the HOV lane distribution to give the reader a sense of variability across tracts. The group with the fewest HOV lane-miles has an average of 10 miles of HOV lanes within a 30-mile radius. The middle group has an average of 116 miles, and the top group

has an average of 287 miles.[27] Census tracts with more HOV lane-miles tend to be more urban, with greater population density, have lower "yes" votes on Proposition 23, higher gasoline prices, higher median home values, and more workers with medium to long commutes by automobile. Census tracts with more HOV lane-miles also have less agricultural industry, which is likely because urban areas tend to have more HOV lanes than rural areas. Census tracts that have more HOV lane-miles have more households without central heat, which may be correlated with coastal locations. Areas with more HOV lane-miles have more racial diversity, also a likely proxy for urban areas. Employment, income, sex, and age do not appear to be substantially different across the groups.

6.3.1 Choice of Covariates

Since we have hundreds of potential explanatory variables and want to avoid over-fitting, we need a methodology to systematically decide which covariates to include. We use classification and regression tree analysis (CART), a data mining technique, in order to determine which covariates to include in the model (Breiman et al., 1984). A classification tree chooses a covariate for the first node that maximizes the information gain in terms of predicting the dependent variable. It splits on the chosen covariate and branches into two daughter nodes. At each of the daughter nodes, another covariate is chosen that maximizes information gain. The covariates chosen by the daughter nodes need not be the same. This procedure continues until the number of data points at a node hits a pre-specified minimum or when no further gain can be made. Lastly, the tree is "pruned" using iterative methods. The main advantage of this methodology as compared to piecewise regression is that it allows for much more flexible functional form (Varian, 2014).

6.4 Methodology

Propensity score matching is a technique used to remove biases in the comparison of treatment groups such that the effectiveness of treatment can be estimated. Standard propensity score matching conditions on a binary treatment variable; however, we are interested in evaluating the effect of a continuous treatment, i.e., HOV lane density. Therefore we follow the generalized propensity score (GPS) matching technique laid out by Hirano and Imbens (2005) to evaluate the effect of HOV lanes on our outcome variable, PEV sales.

This methodology has several advantages. First, we can estimate marginal effectiveness of treatment at different treatment levels rather than estimating the average effect of treatment. This allows us to better understand heterogeneity across treatment groups. Second, this approach is flexible. We assume that after controlling for covariates, treatment follows a Poisson distribution. The GPS is a measure of how likely a census tract is to have a certain number of HOV lane-miles, given its covariates and assuming a Poisson distribution. Such assumptions would not be possible using standard regression techniques.

[27] Note that one mile of six-lane highway with two HOV lanes in both directions would count as 4 miles of HOV lanes.

First, we assume a distribution of treatments, N_i, given covariates, X_i. Each treatment is defined as the number of miles of HOV lanes within a 30-mile radius of the population centroid of a census tract. Covariates include a rich set of demographic, geographic, and socioeconomic variables at the census tract level. Since treatments are count data, we assume that given the covariates, the treatments follow a Poisson distribution:[28]

Equation 6-6

$$N_i|X_i \sim Poisson(\lambda)$$

One of our two key assumptions is weak unconfoundedness, or the independence of treatment given covariates, $Y_i(n) \perp N|X$, where $Y_i(n)$ is our outcome variable, PEV sales. In other words, we assume that after controlling for a rich set of census tract characteristics (listed in tables 6-2 and 6-3), assignment of HOV lanes is independent of PEV sales.[29] (HOV lanes as allocated to those segments of the Interstate network that both i) exhibited chronic congestion and ii) could accommodate a lane expansion or lane reassignment.)

We estimate the parameters of the distribution ($\hat{\lambda}$) using maximum likelihood estimation. We refer to this as the "first estimation stage." We then calculate the estimated GPS, R_i for each census tract i:

Equation 6-7

$$\hat{R}_i = \exp\left(\left(N_i * \ln\left(\hat{\lambda}\right) - \hat{\lambda}\right) - \ln(N_i!)\right)$$

In standard propensity score matching, the propensity score is the predicted probability of treatment. In the continuous case, the generalized propensity score is the probability that treatment level equals N, which in our case is the number of nearby HOV lanes.

Next, we estimate the conditional expectation of the outcome as a function of treatment and GPS:[30]

[28] A Poisson regression results in a lower pseudo R2 than a lognormal or negative binomial regression.

[29] The weak unconfoundedness assumption is not statistically testable. Reverse causality is one potential violation of this assumption. We cannot rule out the possibility that it is PEV sales driving HOV lane construction decisions, however, we find this very unlikely to be the case. Another potential violation of this assumption is correlation between the error terms of the HOV lane variable and PEV sales, which would occur if an omitted variable affected both HOV lanes and PEV sales. We also find this to be unlikely as the decision to construct HOV lanes is made at the state level and affects many local jurisdictions. It is unlikely, though not impossible, that a census tract with a local government keen on promoting local PEV sales influences HOV lane decisions.

[30] We use a fractional polynomial function as described in Section 6.5.3.

Equation 6-8

$$E\left[Y_i \middle| N_i, \hat{R}_l\right] = f(N_i, \hat{R}_l)$$

where $\hat{R}_i$ is the estimated GPS from Equation 6-7. We refer to this as the "second estimation stage." If we assumed a quadratic functional form, for example, Equation 6-8 would be:

Equation 6-9

$$E\left[Y_i \middle| N_i, \hat{R}_i\right] = \alpha_0 + \alpha_1 N_i + \alpha_2 N_i^2 + \alpha_3 \hat{R}_l + \alpha_4 \hat{R}_l^2 + \alpha_5 N_i \hat{R}_l$$

The second key assumption is that the set of covariates is orthogonal to treatment status given GPS, i.e., $X \perp 1\{N = n\}r|(n, X)$. That is, we assume that controlling for GPS removes biases in comparisons across treatment statuses.[31] This assumption, together with the weak unconfoundedness assumption, implies that treatment is unconfounded given GPS. In other words, if our two key assumptions hold, then we remove biases associated with differences in covariates and can compare treatment groups to estimate the causal effect of treatment.

Finally, we calculate the estimated average potential outcome at treatment level n as (using the quadratic example):

Equation 6-10

$$E\left[\hat{Y}(n)\right] = \frac{1}{M}\sum_{i=1}^{M}(\hat{\alpha}_0 + \hat{\alpha}_1 n + \hat{a}_2 n^2 + \hat{\alpha}_3\,\hat{r}(n, X_i) + \hat{\alpha}_4 \hat{r}(n, X_i)^2 + \hat{\alpha}_5 n\hat{r}(n, X_i))$$

where $\hat{r}$ is recalculated for each n using the first estimation stage, $\hat{a}_1$ through $\hat{a}_5$ are the coefficients estimated from the second estimation stage, and M is the total number of census tracts in California.

We calculate the estimated average potential outcome for each level of treatment n in order to estimate the entire dose-response function. The dose-response curve shows how a marginal increase in treatment, i.e., an increase in nearby HOV lanes, impacts PEV sales. We bootstrap the standard errors and cluster the standard errors at the county level.

The GPS technique is fairly new and has been used relatively infrequently in the economic literature. Hirano and Imbens (2005) apply the methodology to estimate the effect of the lottery prize size on winners' subsequent labor earnings. Other studies estimate the effect of duration and quality of training programs (Flores et al., 2012; Kluve et al., 2012; Dammert and Galdo, 2013). There have also been studies in the medical and healthcare literature using GPS (Moodie, Pai, and Klein, 2009; Slavov, 2010; Jiang and Foster, 2013). This chapter is a novel application of GPS with an unusual geographic treatment, miles of HOV lanes. Our unit of

[31] In Section 6.5.2 we find support for this assumption.

analysis, the census tract, allows us to explore geographic heterogeneity by aggregating estimated effects at the metropolitan area level.

6.5 Results

6.5.1 Common Support

When using GPS methods, researchers show what is called "common support" which is necessary for propensity score matching to ensure the sufficiency of comparison groups. Common support requires that there is overlap in the covariate distributions between the treated and untreated populations. For the binary case, one typically compares the propensity score distribution of the treated group with that of the non-treated group and removes observations from either distribution without overlap. For continuous treatment, we can test for common support following the approach of Flores et al. (2012).

We divide observations into three groups of approximately equal size according to treatment level. We evaluate the GPS for all observations at the median treatment of the first group and compare the distribution of this GPS for the first group to the distributions of the other groups. We then evaluate the GPS at the median treatment levels of the second and third groups and repeat the analogous comparison of distributions. Figure 6-2a shows the distribution of the GPS scores for Group 1 versus Groups 2 and 3. Figures 6-2b and 6-2c show the distributions of GPS scores evaluated at the medians of Group 2 and Group 3, respectively.

Figure 6-2a: Common Support

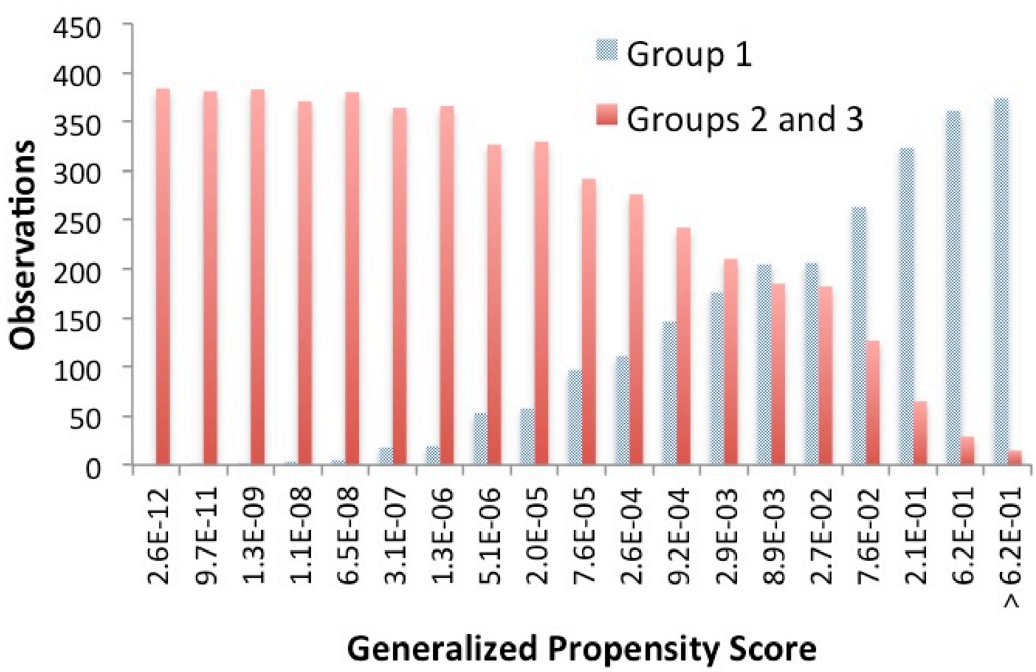


Figure 6-2b: Common Support

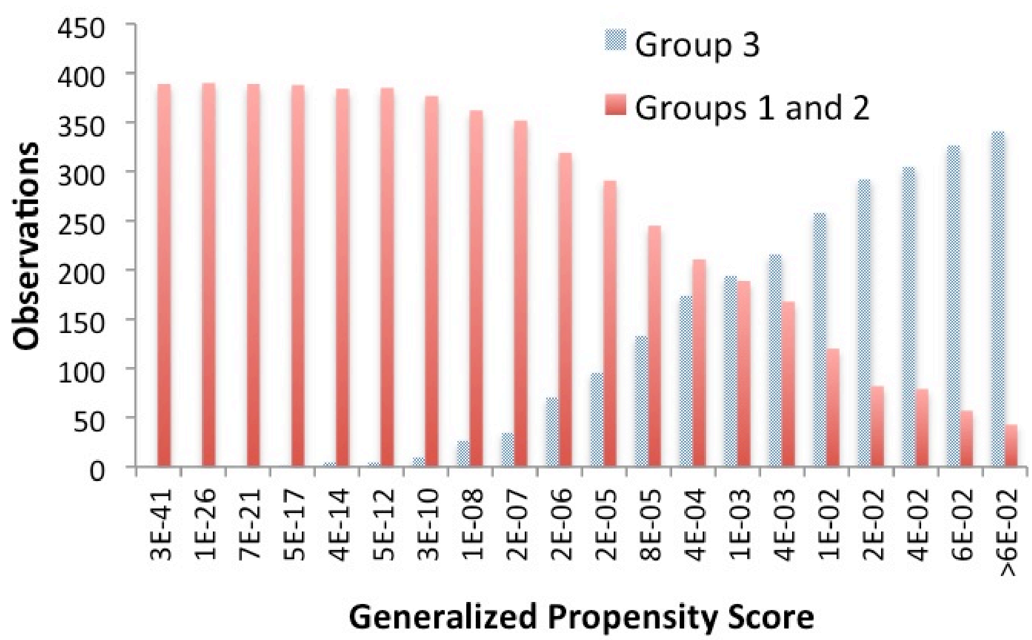
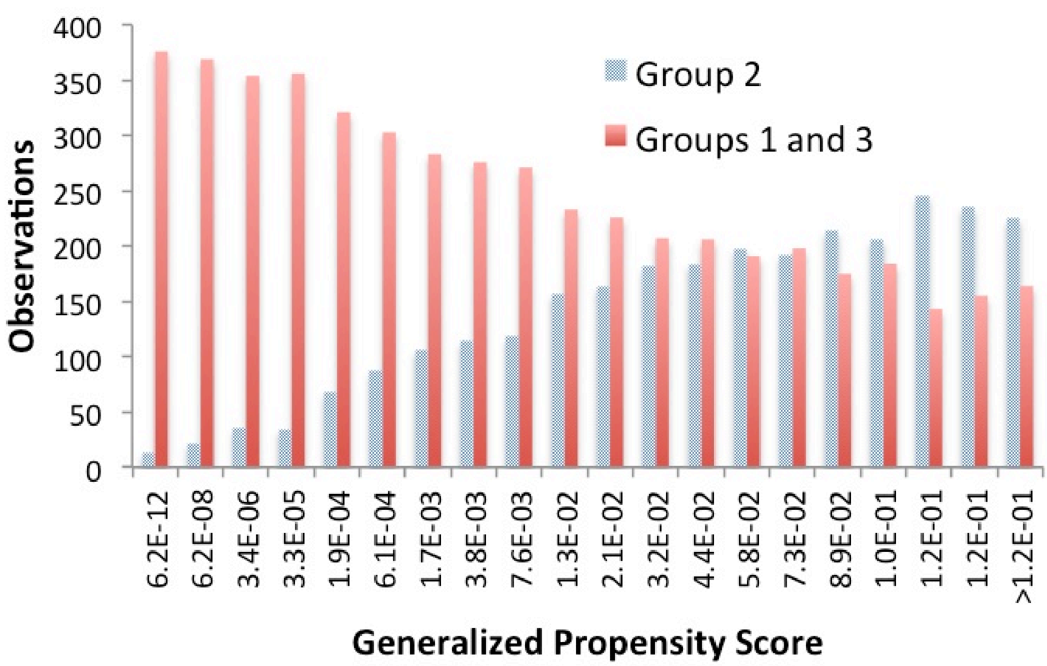


Figure 6-2c: Common Support



There is considerable overlap in the distributions. We exclude from further analysis all observations without overlap; 1,947 tracts were dropped, leaving 6,015 for further analysis. For this very large subset of remaining tracts, we ensure that each census tract can be compared to another census tract with a similar GPS but with a different level of treatment.

6.5.2 Balancing of Covariates

We also test for balancing of the covariates, i.e., that controlling for GPS sufficiently removes biases in covariates. In the binary case we would simply compare the covariate means between the treated and untreated groups before and after matching. In our continuous treatment case, we follow Hirano and Imbens (2005) and use a "blocking on the score" approach. We divide the sample into three intervals according to treatment. Within each interval, we compute the GPS for all observations at the median of the treatment interval. We divide each treatment interval into five blocks by quintiles of the GPS evaluated at the median of the treatment interval. Then we compare the means of a covariate between a given block and observations from different treatment intervals with similar GPS. Lastly, we calculate a weighted average over the five blocks of each treatment interval and use a t-test to determine if the difference in covariate means is significant. We repeat this for every treatment interval and for every covariate. If GPS perfectly balances the covariates, the differences in covariate means should not be statistically greater than zero.

The results of the blocking on the score methodology for testing the balancing property of the GPS are shown in Table 6-A.2 in the Appendix. For each covariate, we test whether the mean of the covariate is significantly different across groups. Without adjusting for the GPS, the t-statistics for the majority of covariates (85%) reject the null hypothesis of equality of means at the 5% level of significance. In other words, before adjusting for the GPS, the treatment and control groups exhibit very different characteristics. After adjustment, however, more than two-thirds (69%) fail to reject the null hypothesis at the 5% level. In other words, after controlling for the GPS, the covariates of the treatment and control groups are very similar. This suggests that adjusting for the GPS greatly improves the balance of the covariates.

6.5.3 First and Second Stage Estimation

Table 6-A.3 in the Appendix shows the results of the first estimation stage, a Poisson regression of the treatment variable on covariates. The coefficients show how different characteristics impact GPS, which is probability of treatment level. The estimation results suggest that census tracts with more commuters and higher population density, among other characteristics, are predicted to have more HOV lane-miles. This is consistent with Figure 6-1a, which shows that more urban areas have more HOV lanes.

Before estimating the second stage, we need to assume a functional form for f in Equation 6-8. Most previous GPS applications (see below) have assumed a low order polynomial. Lower order polynomials are limited in their curvature, while higher order polynomials may fit poorly at extreme covariate values. Fractional polynomials, which allow for both integer and non-integer value polynomials as well as natural logs, are more flexible than standard polynomials (Royston and Altman, 1994). We use an algorithm by Royston and Ambler (1998) for model selection, which selects the multivariable fractional polynomial that best predicts the outcome from the right hand side variables based on goodness of fit statistical tests. Table 6-1, below, shows the results of the second estimation stage, regression of PEV registrations on the fractional polynomial function of treatment and GPS.

Table 6-1: Stage 2 Estimation Results

Outcome	(1) PEV	(2) PHEV	(3) BEV	(4) Prius-Plug-In
$\tilde{T}_1$	13.790***	6.841***	6.740***	2.261***
	(0.709)	(0.330)	(0.442)	(0.126)
$\tilde{T}_1$	-3.997***	-1.871***	-2.064***	-0.568
	(0.208)	(0.097)	(0.130)	(0.037)
$\widetilde{GPS}$	-0.066***	-0.033***	-0.023***	-0.006***
	(0.011)	(0.005)	(0.006)	(0.002)
Constant	13.700	7.140	6.980	2.353
	(0.330)	(0.154)	(0.205)	(0.058)
Observations	5,843	5,843	5,843	5,842
R^2	0.062	0.070	0.042	0.064

Standard errors in parentheses
***p<0.01, **P<0.05, *p<0.1

Where: $\tilde{T}_1 = \left(\frac{Treatment+1}{100}\right) - 1.38$

$$\tilde{T}_2 = \left(\frac{Treatment+1}{100}\right)^2 - 1.91$$

$$\widetilde{GPS} = ln(GPS + 5.98 * 10^{-39}) + 5.22$$

Source: IHS 2010-2015

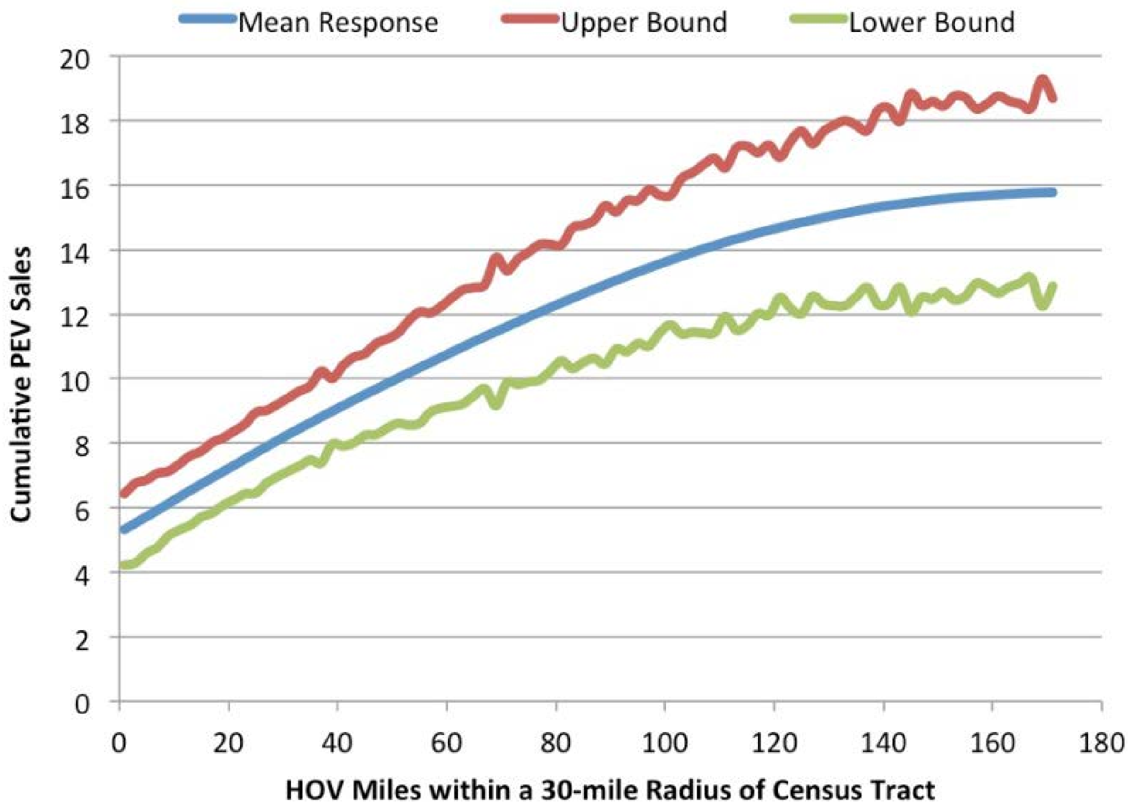
6.5.4 Dose-Response Curves

The generalized propensity score framework essentially removes biases in comparisons across groups by flexibly controlling for GPS, a measure of probability of treatment that takes into account a census tract's characteristics. Once we control for GPS, provided the assumptions in Section 6.4 are satisfied, we can compare PEV registrations across census tracts with different amounts of HOV lane-miles.

We construct a dose-response curve by recalculating the GPS at each level of potential treatment and using the second stage results to predict the average potential outcome, as explained in Section 6.3. Below, Figure 6-3 shows the resulting dose-response curves. The dose-response curves isolate the effects of changes in treatment on PEV sales and are effectively a series of marginal effects. This allows us to predict marginal changes in PEV sales as a function of marginal changes in HOV lane-miles. While the shape of the dose-response curves contain useful information, such as exhibition of decreasing marginal returns, we must use caution in our extrapolations from the dose-response curves.[32] These curves flatten because of decreasing returns. Decreasing returns emerge because adding additional HOV lanes when there are already many (e.g., 140 lane miles) does not provide a much incremental benefit as adding when there are fewer (e.g., 20 mile lanes).

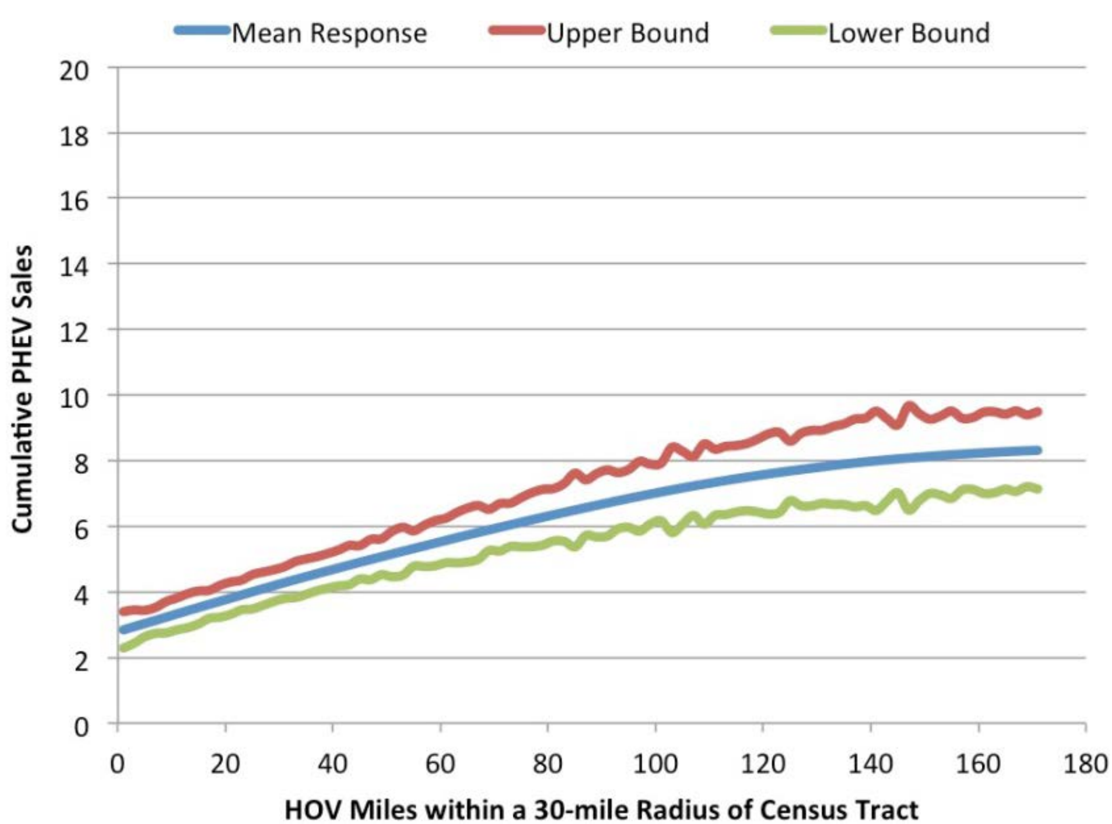
[32] The intercept of the dose-response curve is not estimated separately for each census tract but rather represents the average number of PEV sales to expect in a census tract with average covariate values and no access to HOV lanes. Therefore, our analysis does not allow us to compare PEV sales across different census tracts in the absence of an HOV lane policy.

Figure 6-3a: Dose-response curves; PEV Sales



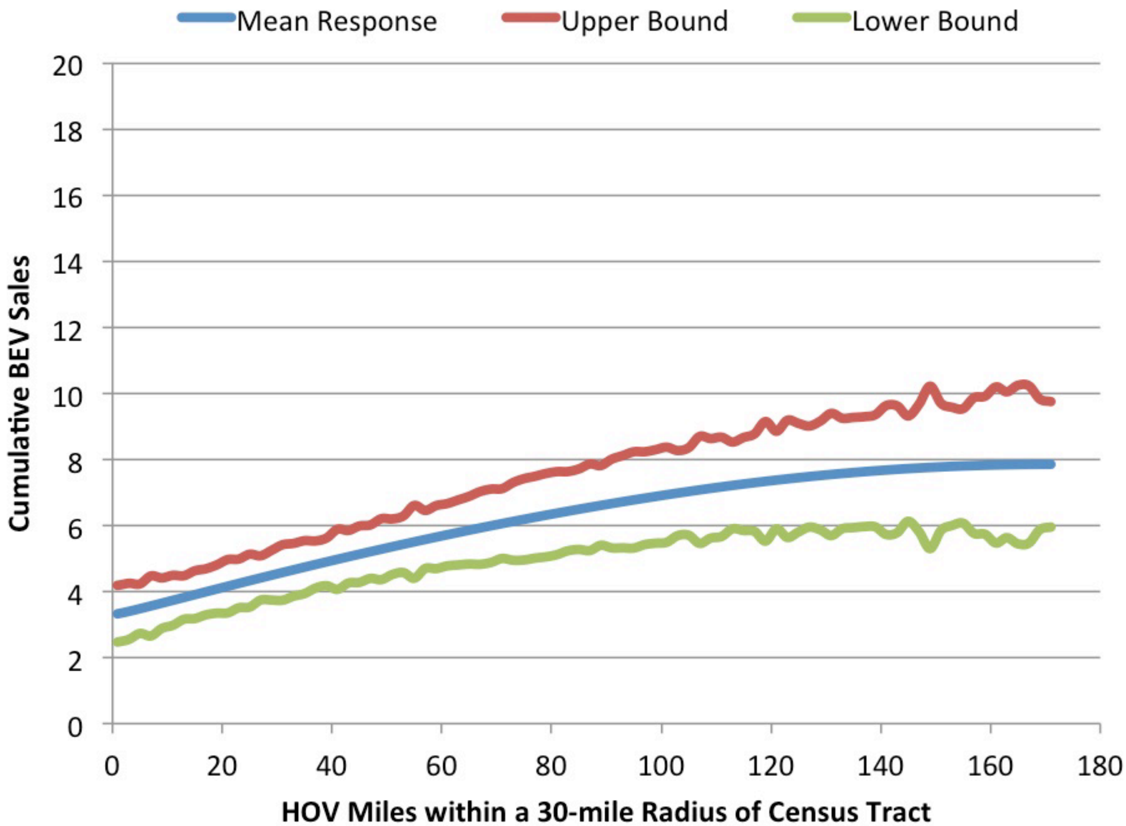
Source: IHS 2010-2015

Figure 6-3b: Dose-response curves; PHEV Sales



Source: IHS 2010-2015

Figure 6-3c: Dose-response curves: BEV Sales



Source: IHS 2010-2015

Figure 6-3a suggests that nearby HOV lane-miles have a statistically significant impact on PEV sales, with the first 20 HOV lane-miles within a 30-mile radius resulting in an additional 2 cumulative PEV purchases. An additional 20 HOV lane-miles (for a total of 40) results in an additional 2 PEV purchases. The curve flattens out after about 140 HOV lane-miles, which results in an additional 10 PEV purchases in total (6 additional after the first 40 miles). These are substantial effects, especially when considering that census tracts are generally only a few square miles in area, meaning that an HOV lane-mile could be in the 30- mile radius of many census tracts.

Figures 6-3b and 6-3c show the dose-response curves for PHEVs and BEVs, respectively. These two dose- response curves have very similar shapes and flatten out at approximately the same point, after 140 HOV lane-miles. The main difference is that the error bounds on the PHEV curve are narrower. The results suggest that we are measuring the relationship between PHEV sales and access to HOV with greater precision. Our broader results here suggest that the impact of the HOV lane policy is similar across vehicle technologies, and one technology type or model does not appear to drive the main result in Figure 6-3.

6.5.5 Simulations

The first stage estimation coefficients in Table 6-A.3 show which covariates are associated with higher numbers of HOV lanes and, therefore, higher generalized propensity scores. The second stage estimation results in Table 6-1 show that more HOV lane-miles (that is, a higher level of treatment) are associated with higher PEV registrations, with the negative quadratic term suggesting decreasing marginal returns to treatment. Table 6-2, below, summarizes relevant characteristics for California's largest metropolitan areas.[33]

Table 6-2: California Metropolitan Area Characteristics in 2013*

	San Diego	Los Angeles	San Francisco	Sacramento
PEV Registrations (cumulative)	8.8	6.7	8.3	4
PHEV Registrations (cumulative)	3.8	4.4	3.7	2.1
BEV Registrations (cumulative)	5.3	2.8	4.9	2.2
HOV Miles (30-mile Radius)	10	229	98	38
GPS	0.004	0.005	0.007	0.023
Population	4,949	3,819	4,171	4,485
Commuters	2,285	1,791	2,270	1,886
Population Density (per sq. mile)	7,129	17,334	28,818	5,207
Area (Land, sq. mile)	6.7	0.4	0.2	3.1
Prop 23 "Yes" Vote	43%	29%	18%	37%
Avg Gas Price ($)	3.63	3.66	3.7	3.44
Avg Electric Price (cents)	6.8	12.6	11.9	11.9
Commute by Auto: Under 15min	21%	15%	8%	21%
Commute by Auto: 30-60min	25%	30%	17%	26%
Commute by Auto: Over 60min	4%	8%	4%	5%
Level 1 Chargers (5-mile Radius)	2	6	71	4
Level 2 Chargers (5-mile Radius)	58	73	166	47
DC Chargers (5-mile Radius)	0.4	0.5	0.7	0.4
All characteristics shown are the mean across census tracts in each metropolitan area.				

Source: IHS 2010-2015; American Community Survey 2013-2015

Los Angeles has the highest average number of HOV lane-miles within a 30-mile radius of a census tract at 229 miles, followed by San Francisco (98), Sacramento (38), and San Diego (10). Census tracts in Sacramento and San Francisco have the highest GPS on average, and those in San Diego and Los Angeles have the lowest. The first stage estimation results in Table 6-A.3 suggest that census tracts with more commuters, greater population density, higher average gasoline prices, and more drivers with daily commutes greater than a half hour, among other characteristics, will have higher GPS.

The level of actual treatment, or HOV lane-miles, will determine where a census tract is located on the dose-response curve and what marginal effects are relevant. Census tracts with fewer than 60-80 HOV lane-miles will be located on the linear part of the dose-response curve, while those with more HOV lane-miles will be located on the flat part of the dose-response curve.

[33] A more thorough characterization can be found in Appendix Table 6-A.4.

Therefore, we would expect areas with fewer HOV lane-miles, such as San Diego and Sacramento, to be responsive to marginal changes in HOV lane-miles, and we would expect areas with very many HOV lane-miles, such as Los Angeles, to be relatively unresponsive to marginal changes in HOV lane-miles.

We use our results to simulate how an increase or decrease in HOV lane-miles would affect PEV sales in California's largest cities. For each census tract, we increase or decrease the number of HOV lane-miles by a given percent and predict the number of PEV sales using the second stage estimates shown in Table 6-1. We are then able to integrate PEV sales over all census tracts in a given city. Table 6-3 shows how cumulative PEV sales are predicted to change in percentage terms if the number of miles of HOV lane-miles in a city increased or decreased.

Table 6-3: Simulation Results

PEV Sales (Feb 2010 - Dec 2013), % of Actual					
HOV Lanes, % of Actual	California	San Diego	Los Angeles	San Francisco	Sacramento
70%	93.8%	94.0%	96.4%	84.0%	83.1%
80%	96.2%	96.0%	98.3%	89.9%	87.9%
90%	98.3%	98.0%	99.4%	95.2%	94.0%
100%	100.0%	100.0%	100.0%	100.0%	100.0%
110%	101.4%	101.9%	100.4%	104.2%	105.8%
120%	102.6%	103.9%	100.5%	107.7%	111.4%
130%	103.6%	105.8%	100.6%	110.6%	116.9%

Source: IHS 2010-2015; American Community Survey 2013-2015

Los Angeles seems to already be at the flat part of the dose-response curve, where HOV lane density is already high enough in most census tracts that additional HOV lane-miles do not further impact PEV sales. Los Angeles has the most HOV lane-miles out of the four cities. This suggests the Los Angeles area is relatively saturated in HOV lanes, such that all consumers will be less responsive to further increases in HOV lane access. If there were 30% fewer HOV lane-miles in Los Angeles, it would still have more HOV lane-miles than any other city in California. Importantly, this finding does not mean that California's HOV lane policy has not induced PEV sales in Los Angeles. Indeed, HOV lane access may have motivated a substantial number of PEV sales in the area, but our analysis identifies only the marginal effects of marginal changes in HOV lane access.

San Francisco and Sacramento PEV sales are predicted to be the most sensitive to changes in HOV lane density. A 10% decrease (increase) in HOV lane-miles is associated with a 4.8% decrease (4.2% increase) in San Francisco and a 6% decrease (5.8% increase) in Sacramento. That PEV sales are lower in these cities than San Diego and Los Angeles and also more sensitive to HOV lane density suggests that a larger proportion of marginal PEV sales in San Francisco and Sacramento are motivated by drivers who are responsive to marginal increases in access to HOV lanes.

San Diego has both the highest number of PEV registrations and the lowest number of HOV lane-miles out of all four metropolitan areas. That San Diego PEV registrations are so high suggests that factors other than HOV lane access are motivating San Diego drivers to adopt PEVs (such as perhaps lower electricity prices than other regions). The lower marginal responsiveness of San Diego drivers to changes in HOV lanes is likely due to the fact that San Diego has so few HOV lane-miles to begin with. We might expect drivers' valuation of this policy to jump up once a certain minimum scale of HOV travel lanes is achieved. In San Diego a 30% increase in HOV lane-miles only translates into about 3 additional miles of HOV lanes near each census tract.

6.6 Caveats and Conclusion

We have developed an approach that identifies both a state-wide average marginal effect of HOV lane access on PEV sales and location-specific estimates that accommodate local variation on policy treatment. Our findings (or estimated treatment effects) are conditioned on several factors. First, our estimated marginal effects are for a PEV market and a policy that has been in place for four years. Therefore, we are measuring a treatment effect over a considerable period of time for early and middle- market adopters, who may be less responsive to the time and cost savings associated with increased HOV lane access than will be future PEV adopters. Our approach, when combined with a discrete policy change (such as the creation of new additional HOV lanes), may allow future researchers to identify per year effects rather than cumulative effects. Second, the impacts of this policy may depend upon both other policies and market conditions that affect the total costs of owning PEVs. Changes in PEV market prices relative to conventional vehicles, gasoline and electricity prices, as well as vehicle purchase incentives and refueling infrastructure subsidies could affect our findings. Lastly, as discussed in our theoretical model, as congestion changes in existing HOV lanes, so too will drivers' willingness to pay to access these lanes.

6.7 References

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Chapter 7: Comparing Demand for Battery Electric & Plug-in Hybrid Vehicles: A Stated-Preference Analysis

7.1 Introduction

What factors best explain how current and future household demand for BEVs differs from demand for PHEVs? Our analysis using neighborhood-scale characteristics in section 4.5 could explain little of the observed variation across neighborhoods. This is not surprising since the models using neighborhood variables could not incorporate variables on *household preferences* or *vehicle attributes*. Important explanatory variables could include battery range, the cost of traveling a mile on gasoline, the cost of traveling a mile on electricity, attitudes toward improving air quality, and other features of the vehicle.

In this chapter we develop models based on a statewide household survey that enables us to incorporate these variables into our analysis of BEVs and PHEVs. Importantly for policy analysis, our study will also estimate households' price elasticities and willingness to pay for BEVs and PHEVs so that we can analyze changes in PEV rebate levels for households of different income levels in Chapter 8. It should also be noted that this was an independent survey operated and funded by the University of California, Los Angeles Luskin Center for Innovation and was not designed by ARB. Because revealed preference data that enables a researcher to observe household choice among a known choice of actual vehicles including PEVs is not available, we employ a state-of-the-art, stated-preference approach based on a sample of 1,200 California new car buyers. To evaluate the validity of these stated preferences we compare both our survey sample of consumers and our predicted vehicle choices with actual population and market data in Appendix 7-A.

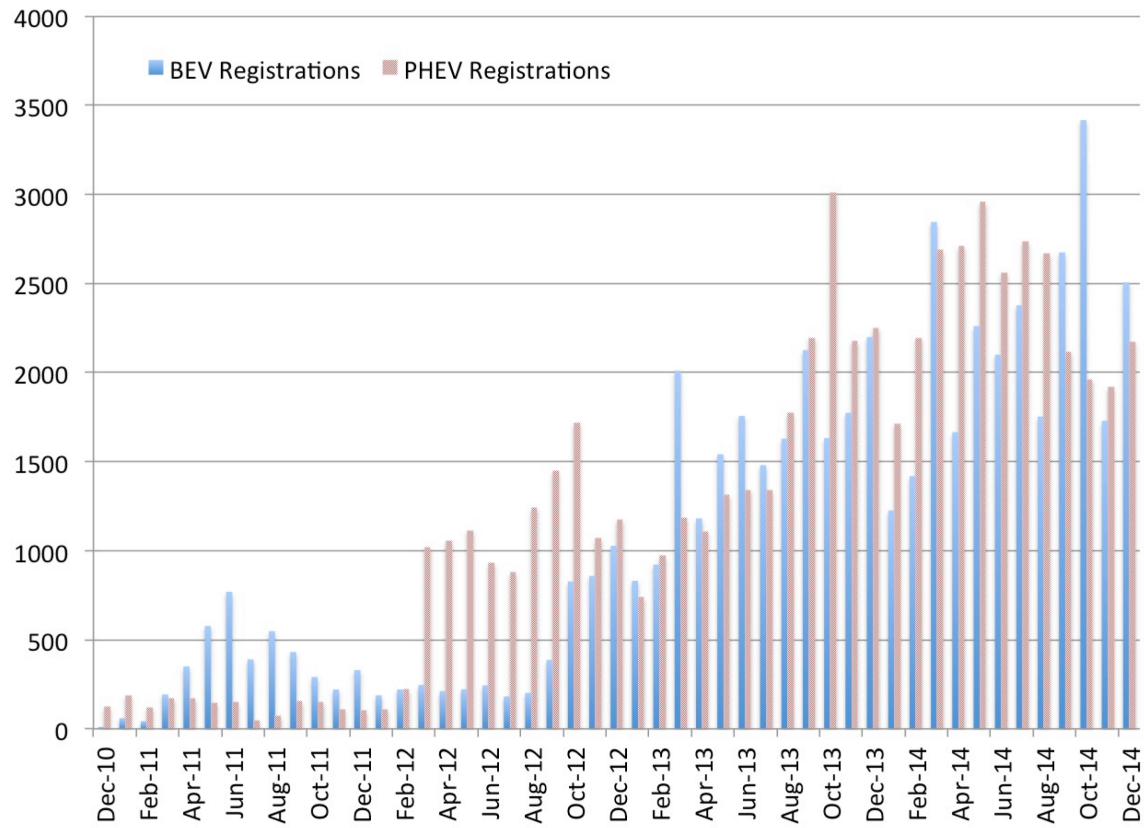
Background. Automakers have added plug-in hybrid electric vehicles (PHEVs), which may be fueled by either electricity or gasoline, to the early mix of battery electric vehicles (BEVs), which are fueled only by electricity. See Table 7-1 below, which describes the models introduced from 2010-2015, to which should be added the Nissan LEAF introduced in 2010. By adding PHEVs, automakers sought to eliminate consumers' "range anxiety" associated with the limited travel range of smaller-battery BEVs. PHEVs also represented a vehicle design innovation that enabled many automakers to adapt pre-existing vehicle designs to plug-in electric refueling, thus eliminating their need to design entirely new models. For instance, there are now PHEV versions of the Ford Fusion, Honda Accord, and Porsche Panamera. The attractiveness to automakers of PHEVs relative to BEVs has been revealed by the decision to introduce a substantial number of PHEVs to the market (see Table 4-1) including newer entrants like the

Audi A3 e-tron and Hyundai Sonata Plug-in. Consumers have thus far exhibited a similar preference for PHEVs and BEVs as shown in Figure 7-1.

Table 7-1: PEV Model Introductions

2010 - 2011		
Model	**Make**	**PEV Type**
Roadster	Tesla	BEV
Leaf	Nissan	BEV
Estar	International	BEV
Volt	Chevrolet	PHEV
Fortwo	Smartcar	BEV
Transit Connect	Azure	BEV
I-Miev	Mitsubishi	BEV
2012 - 2013		
Model S Variations	Tesla	BEV
2012 smart fortwo ed.	Daimler	BEV
e6	BYD	BEV
Chevy Spark	GM	BEV
Scion iQ	Toyota	BEV
RAV4 EV	Toyota	BEV
C-Max Energi	Ford	PHEV
Fusion Energy	Ford	PHEV
Fit EV	Honda	BEV
GCE	Amp	BEV
MLe	Amp	BEV
Accord PHV	Honda	PHEV
F3DM	BYD	PHEV
F6DM	BYD	PHEV
500 Elettrica	Chrysler-Fiat	BEV
Cadillac ELR	GM	PHEV
Prius Plug-in Hybrid	Toyota	PHEV
Panamera	Porsche	PHEV
Focus Electric	Ford	BEV
2014 - 2015		
i3	BMW	BEV
E-Golf	VW	BEV
i8	BMW	PHEV
Cayenne S E-Hybrid	Porsche	PHEV
918 Spyder	Porsche	PHEV
Soul EV	Kia	BEV
B-Class Electric	Mercedes-Benz	BEV
A3 e-tron	Audi	PHEV
Model X	Tesla	BEV
A3 e-tron	Audi	PHEV
Sonata Plug-in Hybrid	Hyundai	PHEV

Figure 7-1: PEV Registrations in California by Month



Source: IHS 2010-2014

Researchers have undertaken studies of consumer demand for BEVs (Bunch et al., 1993; Brownstone, Bunch, and Train, 2000; Hidrue et al., 2011), however, research on PHEV demand remains limited. Most existing research studies were implemented before PHEVs were commercially available and they focused on design priorities for vehicle attributes (Kurani, Heffner, and Turrentine, 2008; Axsen and Kurani, 2009) as well as qualitative market trial studies (Caperello and Kurani, 2012; Graham-Rowe et al., 2012). The most comparable study to the work we discuss here is that of Axsen and Kurani (2013), who survey a sample of recent new car buyers in San Diego. They asked buyers to play a design game where they assembled vehicles by allocating values to different attribute options. They find that PEVs are preferred to regular hybrids which in turn are preferred to regular vehicles. Within PEVs as a group, PHEVs are preferred to BEVs in choice exercises.

Several important questions relevant to understanding the need for, and design of, public policies remain unanswered. A critical empirical question is what vehicle attributes drive differences in consumer demand for BEVs, PHEVs, HEVs and internal combustion engines (ICEs) and how large those differences are, all else being equal? Answering this question helps us to understand the importance of the PHEV as a vehicle innovation in the growth of the plug- in electric vehicle market. This relative preference information is also critical in determining whether vehicle purchase incentives will be needed to encourage PHEV purchases, and if so, how effective they are likely to be offsetting the value difference (e.g., compensating for consumer utility differentials) across types of vehicles. Lastly, understanding consumers' willingness to pay differential enables economists to evaluate the size of "free rider" losses[34] associated with vehicle purchase incentives for BEVs versus PHEVs, as well as the total public revenues needed to support these rebate policies.[35]

Beyond vehicle purchase incentives, there are also important questions about how differences in consumer demand for BEVs and PHEVs interact with other public policy incentives. For example, some researchers have suggested that demand for BEVs, relative to PHEVs, may be more sensitive to the presence of residential and publicly-accessible recharging infrastructure since BEVs cannot operate using gasoline (Egbue and Long, 2012; Khan and Kockelman, 2012). If true, this might explain how the policy provision for charging infrastructure and PEV-friendly buildings will affect the relative rates of purchase of BEVs and PHEVs. In addition, many states allow BEVs and PHEVs to use high occupancy vehicle (HOV) lanes. When predicting PEV market growth impacts, it may be useful to policy-makers to better understand if there are differences in how HOV access affected demand for BEVs versus PHEVs.

Better understanding of consumer valuation of PEVs and their attributes can also inform us of how this market is likely to evolve as newer vehicle models come to market. For example, estimating consumer preferences for PEV mileage range can help in understanding how consumer demand will likely respond to second-generation, extended-range PEVs that become available in the next several years.

Using stated preference data from a survey of California new car buyers, we estimate discrete choice models that allow us to compare demand for BEVs, PHEVs, and conventional ICE vehicles. We compare these stated preference data with actual market data, (which reveals observed consumer preference behavior), at several junctures to evaluate their validity, including vehicle preferences and socioeconomic characteristics. This is one of the first studies to investigate relative demand for different PEV technologies. Our analysis also uses innovative experimental design techniques, including a Bayesian D-efficient design that enables a more efficient estimation, as well as a pivoting on preference and prices for non-PEV vehicles in order to make the choices faced by survey respondents more realistic.

We estimate three models that allow us to explore diversity of preferences for PEVs from several angles. First, we estimate a mixed logit model that allows for the estimated preference parameters to randomly vary. Second, we estimate an alternative specific constant logit, which provides insight into what consumer characteristics tend to be associated with different aspects

[34] A free rider loss occurs in rebate programs when a program gives rebates to consumers who would have purchased the vehicles even in the absence of a rebate. These consumers are said to be "free riding" on the rebate program.

[35] DeShazo, Sheldon, and Carson (2015) find that rebates are more cost-effective not only when they target consumer segments with more marginal consumers, but also when they target segments with fewer infra-marginal consumers. For example, they find that it is optimal to allocate higher rebates to BEV purchases than to PHEV purchases since there are more infra-marginal PHEV purchasers who receive the rebate and who would have purchased the PHEV even in the absence of the rebate.

of the preference parameter distributions. Finally, we estimate a latent class model, which allows us to uncover customer profiles of market segmentation. This latter model groups similar consumers together based on type of preferences and tradeoffs they are observed making, which will help us determine the size of the consumer groups with a preference for BEVs and PHEVs.

7.2 Survey Design and Data

In 2014 we administered an online survey to a representative sample of Californian new car buyers and obtained a sample of 1,261 completed surveys.[36] GfK's KnowledgePanel is a probability-based panel designed to be statistically representative of the California population. Because all KnowledgePanel households were selected randomly with a known probability of selection, KnowledgePanel estimates can be used with the statistical confidence required.

Initially using random-digit-dialing (RDD), KnowledgePanel is now continuously maintained using the United States Postal Service's Delivery Sequence File. This file is essentially a complete list of all California residential households, including households that are cell phone-only and often missed in RDD sampling. Persons in selected households are then invited to participate in GFK's Web enabled panel. Those who agree to participate, but are not already on the Internet, are sent a laptop computer and receive an Internet service connection provided and paid for by GfK. People who already have computers and Internet service are permitted to participate using their own equipment.

Latino Subsample: The sample for KnowledgePanel Latinos uses a dual frame design. The main sample is recruited through the mail using English and Spanish materials. This address-based sample (ABS) is drawn from the U.S. Postal Service's Computerized Delivery Sequence file that covers approximately 97% of the physical addresses. The ABS mail sample represents all households whether they have only cellular telephone service, a landline telephone or no telephone service. The ABS sample is further supplemented with a smaller RDD telephone recruitment that specifically targets high density Latino areas. This RDD sample is designed to exclusively recruit additional Spanish-dominant households. As a result, KnowledgePanel Latino has the most complete coverage of the California Latino population. The survey first gathered household, vehicle, and demographic data. Next, the survey elicited body and brand preferences. Respondents were asked to choose the top two vehicle body types (out of twelve options) they were most likely to select for their next new vehicle purchase, as shown in Figure 7-2.

Then respondents were asked to select the top three brands (out of the twenty most popular brands by sales volume in California in 2012) they were most likely to select for their next new vehicle purchase, as shown in Figure 7-3.

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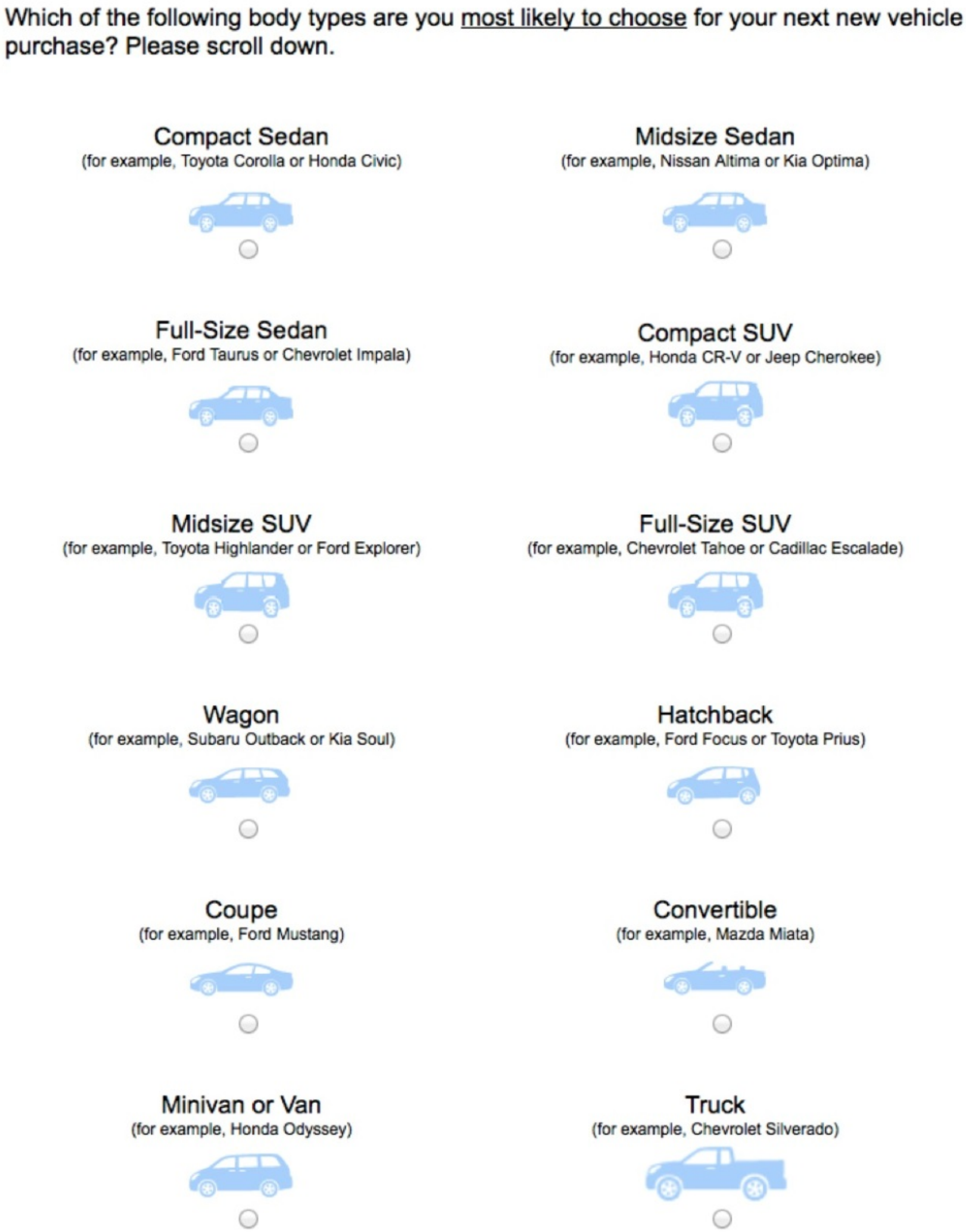
[36] Of the respondents who completed an initial screener, approximately 42% both qualified as potential new car buyers and completed the survey.

Once we understood households' preferences for the body and brand, we constructed a set of equivalent BEV and PHEV vehicles for these body types and brands. In our stated preference choice experiments, we then mix these BEV and PHEVs models in with equivalent ICE models. In this way our survey approach is forward-looking in that it elicits consumers' preferences for BEV and PHEV types that are not yet available but are likely to be in the coming market. This allows us to present PEV choices that go beyond the two dozen or so models that were currently available to consumers in order to explore their preferences more thoroughly.

Figure 7-2: New Car Buyer Survey: Body Choice



Which of the following body types are you most likely to choose for your next new vehicle purchase? Please scroll down.

Compact Sedan
(for example, Toyota Corolla or Honda Civic)

Midsize Sedan
(for example, Nissan Altima or Kia Optima)

Full-Size Sedan
(for example, Ford Taurus or Chevrolet Impala)

Compact SUV
(for example, Honda CR-V or Jeep Cherokee)

Midsize SUV
(for example, Toyota Highlander or Ford Explorer)

Full-Size SUV
(for example, Chevrolet Tahoe or Cadillac Escalade)

Wagon
(for example, Subaru Outback or Kia Soul)

Hatchback
(for example, Ford Focus or Toyota Prius)

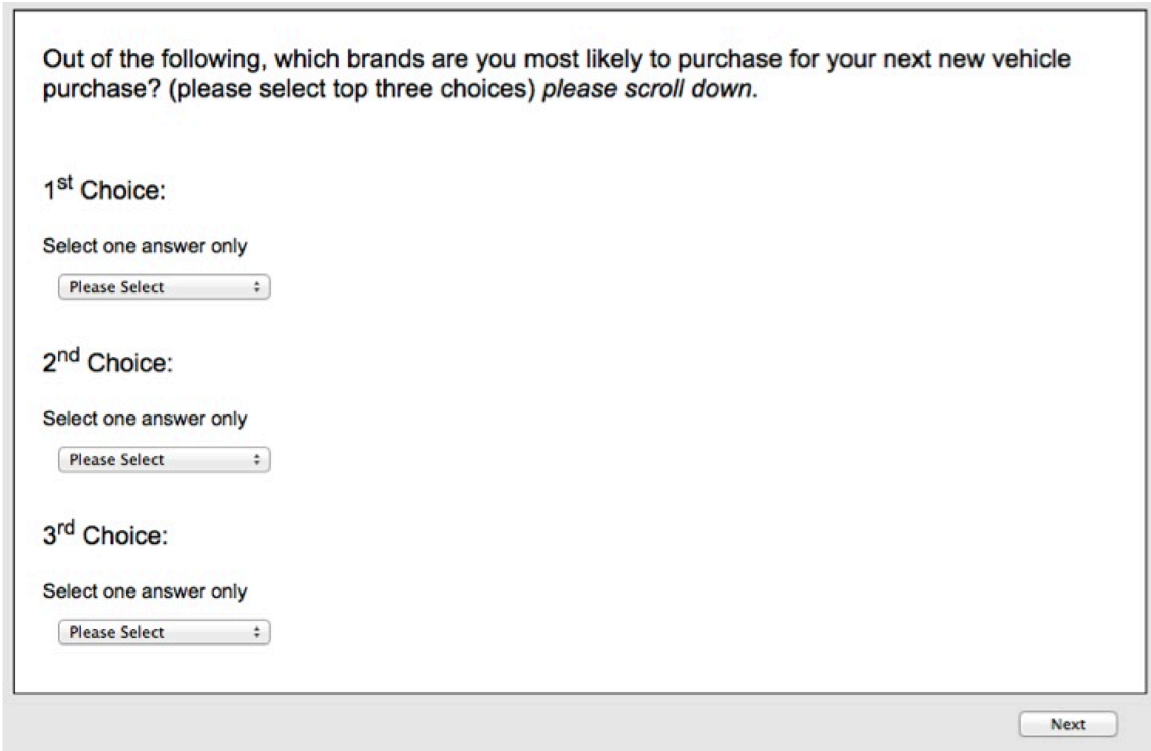
Coupe
(for example, Ford Mustang)

Convertible
(for example, Mazda Miata)

Minivan or Van
(for example, Honda Odyssey)

Truck
(for example, Chevrolet Silverado)

Figure 7-3: New Car Buyer Survey: Brand Choice



Out of the following, which brands are you most likely to purchase for your next new vehicle purchase? (please select top three choices) *please scroll down.*

1st Choice:

Select one answer only

Please Select

2nd Choice:

Select one answer only

Please Select

3rd Choice:

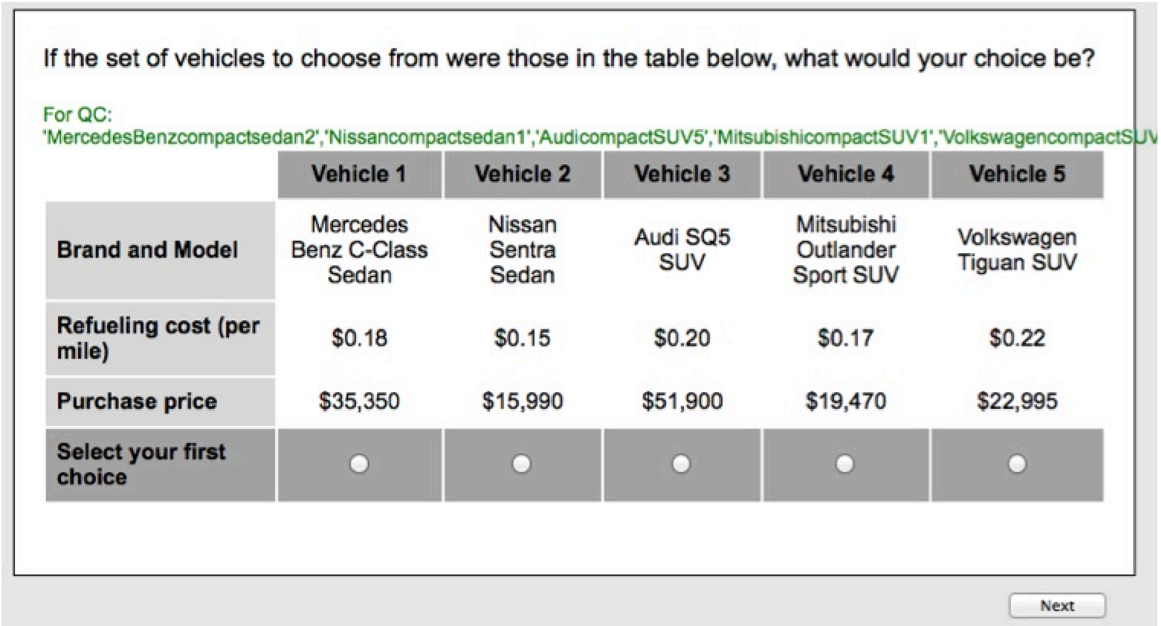
Select one answer only

Please Select

Next

Next, respondents were shown four sets of five vehicles, as displayed in Figure 7-4, and in each set were asked to choose which of the five vehicles they were most likely to select for their next new vehicle purchase. The total set of twenty vehicles respondents chose from included only conventional vehicles (including internal combustion engine vehicles, hybrid electric vehicles, and diesel-fueled vehicles) on the new vehicle market as of the fall of 2013. It included specifically the vehicles that are of both the top brand and top body selected by respondents. The remainder of the twenty included a random draw of vehicles that are of the top body choice and second or third brand choice, or of the second body choice and top brand choice. In cases where the set of vehicles that meets these criteria is less than twenty, the remainder of the vehicles was a random selection of vehicles that are of either one of the top body selections or of the top brand selections.

Figure 7-4: New Car Buyer Survey: Top Vehicle Choice


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

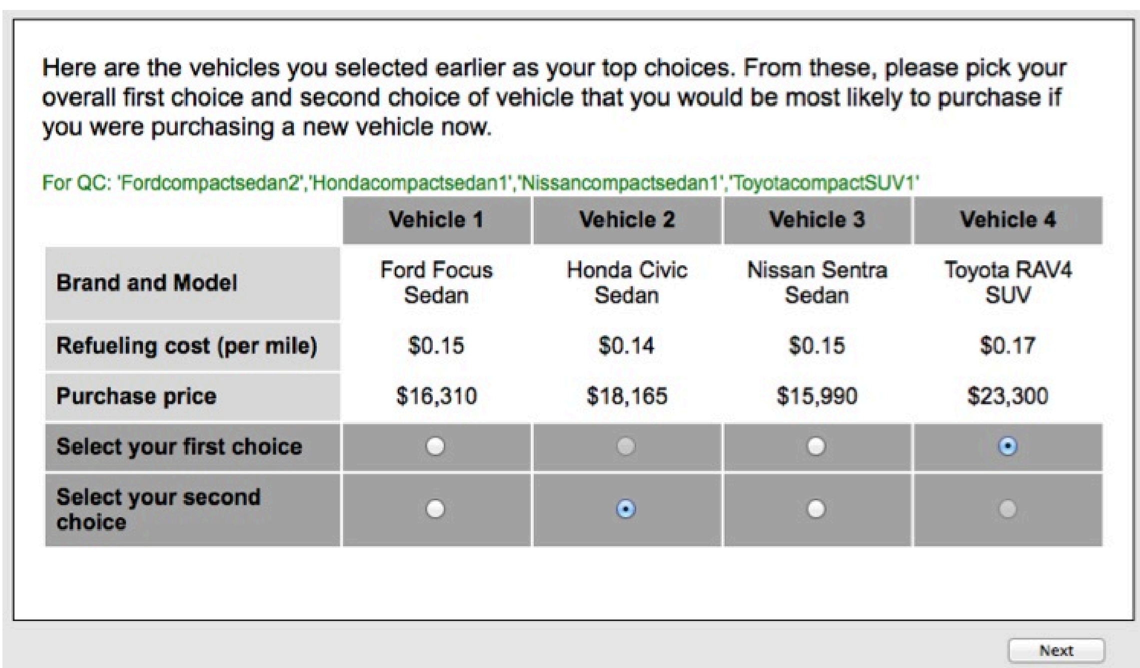
For QC: 'MercedesBenzcompactsedan2','Nissancompactsedan1','AudicompactSUV5','MitsubishicompactSUV1','VolkswagencompactSUV

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

Next

Finally, respondents were asked to choose which one of the four vehicles chosen as top picks out of the twenty vehicles in the previous five questions they would be most likely to select for their next new vehicle purchase, as shown below in Figure 7-5. This ‘top’ vehicle and its characteristics are carried through to subsequent questions in the survey.

Figure 7-5: New Car Buyer Survey: Top Vehicle Choice


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

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

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

Next

Respondents were provided with information on BEV and PHEV technologies and introduced to PEV attributes, including refuel price, electric range, and HOV lane access. Finally, respondents were asked to choose between the conventional version, two BEV versions, and two PHEV versions of the vehicle they previously indicated as their top choice. (This approach presents consumers with a wide set of brand and body types containing BEV and PHEV technologies that are likely to become available.)

In each choice set the first column displayed the conventional vehicle, and we randomized whether the two BEVs or PHEVs appeared in the subsequent columns. Attribute levels vary for each vehicle version as shown in Table 7-2, with the hypothetical price oriented in reference to the price of the existing conventional vehicle. An example choice set is shown in Figure 7-6. So these prices are based on current brands and models which are then adjusted or pivoted upward by varying higher percentages.

Table 7-2: Attribute Levels

Purchase Price[1] (% of conventional)				
Gasoline	100%			
BEV	105%	115%	125%	150%
PHEV	105%	115%	125%	150%
Gasoline Refuel Cost ($ per gal)				
Gasoline[2]	$4.00	$4.40	$4.80	$5.60
BEV	n/a			
PHEV[3]	$2.00	$2.20	$2.40	$2.80
Electric Refuel Cost[4] ($ per gal equivalent)				
Gasoline	n/a			
BEV	$0.90	$1.10	$1.50	$2.50
PHEV	$0.90	$1.10	$1.50	$2.50
Gasoline Range (miles)				
Gasoline	300			
BEV	0			
PHEV	300			
Electric Range (miles)				
Gasoline	n/a			
BEV	50	75	100	200
PHEV	10	20	40	60
HOV access				
Gasoline	no			
BEV	no, yes			
PHEV	no, yes			

[1]The respondent sees price in dollars. For example, a respondent who selected a conventional model that costs $30,000 would see BEV and PHEV versions of that model that cost $31,500, $34,500, $37,500, or $45,000.
[2]At the time the survey was administered average gasoline cost in California was approximately $4 per gallon.
[3]The average gasoline fuel economy of PHEVs as of December 2013 was 41mpg, which is roughly double the fuel economy of our gasoline vehicle universe of 20mpg. Therefore we choose a baseline refueling cost for PHEVs that is half that of gasoline vehicles.
[4]At the time the survey was administered, the average overnight electricity rate in California was roughly 16 cents per kilowatt hour (kWh) and the average vehicle economy of electric vehicles was 3.5 miles per kWh, suggesting an

average cost per electric mile of $0.046. The average cost per mile of gasoline vehicles in our vehicle universe is ($4/gal)/(20mi/gal) = $0.20 per mile. Thus on average, refueling cost for electric miles is 23% of the $4 per gallon refueling cost for gasoline miles, or $0.92/gal. Therefore we choose a baseline electric refueling cost of $0.90 per gallon equivalent.

Our Conceptual Strategy. Our objective in designing these choice sets is to discover how consumers trade off different vehicle attributes. In this chapter we are especially focused on how much more or less consumers would pay (i.e. the price of the vehicle) depending on whether the vehicle is a BEV, PHEV or conventional vehicle, while controlling for the other attributes of the vehicle. To discover these tradeoffs for a consumer, our strategy is to vary the attribute levels so that we may identify or "map out" their tradeoffs using statistical models. For example, holding all other attributes of a vehicle at a common level, we want to discover both when a consumer will say "yes" to a price for a BEV and when they will say "no" thereby rejecting in favor of another option. It is important to recognize that this process of discovering the consumer's internal value that they are willing to pay for a vehicle does not require us to use actual vehicle market prices. In fact, using only actual market prices would prevent us from "mapping out" prices that a consumer would say both "yes" and "no" too. So the reader should not be concerned that when we will select a range of hypothetical prices that diverge from actual market prices that the validity of our findings are jeopardized.

Figure 7-6: New Car Buyer Survey: PEV vs. Conventional Vehicle Choice Module

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

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

Next

Note: dual-fuel is the same as PHEV. This definition was used to make the PHEV concept more accessible and clearer to respondents. We use NGENE software to design the choice experiment. The efficiency of an experimental design can be greatly improved if we know the approximate magnitude or even the sign of the true parameters (Scarpa and Rose, 2008). For example, by assuming that the coefficient on price is negative, or that consumer utility for an alternative is reduced as that alternative gets more expensive, we no longer need an experimental design that can distinguish between a negative or positive coefficient, but can instead more precisely estimate a negative coefficient.

Specifically, we use an algorithm in NGENE that allows us to maximize the amount of information we are able to extract from our choice experiment by minimizing the variance-covariance estimator of the vector of utility function coefficients. The algorithm searches through potential experimental designs with different combinations and levels of attributes. We select the experimental design with the smallest determinant of the asymptotic variance-covariance matrix, also known as the D-error.[37] To further increase the efficiency of the design, we specify Bayesian priors. That is, for each coefficient that we seek to estimate, we specify an assumed a priori distribution based on existing market data and prior PEV studies. We base these assumptions on parameter estimates from earlier studies looking at PEV attributes (Bunch et al., 1993; Golob et al., 1993; Brownstone, Bunch, and Train, 2000; Ewing and Sarigöllü, 2000; Hidrue et al., 2011; Qian and Soopramanien, 2011; Achtnicht, Bühler, and Hermeling, 2012).

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

To incorporate the pivoting price attribute levels in the experimental design, NGENE's algorithm uses relative attribute levels rather than absolute attribute levels for price. However, in calculating the efficiency of the design, the algorithm must assume some reference level. Therefore, we assume four different segments: 1) economy and compact cars, 2) mid-size and large cars, 3) SUVs, trucks, and minivans, and 4) luxury vehicles. For each segment we assume the price is the average of that vehicle type from the new vehicle universe. The algorithm uses a model averaging approach according to the actual market shares of the four segments.

[37] For more details see Scarpa and Rose (2008).

Table 7-A.1 in the Appendix gives definitions of all the variables used in our analysis. Most of these variables were collected in the survey. We obtained average gasoline prices in December 2013 by census tract from Gas Buddy Organization Inc. From the U.S. Department of Energy's Alternative Fuels Data Center we obtained a measure of publicly-available PEV charger density, which we define as the number of level 2 chargers within a 5-mile radius of the population centroid of a census tract as of December 2013.

7.3 Model Specification

The standard multinomial logit can model the probability of selecting a vehicle over other alternatives. In this model, a respondent selects the vehicle that gives her greater utility than any other available alternative while also considering her budget constraint based on income. The utility of each alternative is a function of its attributes. The estimated coefficients tell us how a change in each attribute (e.g., an increase in range) impacts utility.

Individual n receives utility u_{ni} from choosing alternative i:

Equation 7-1

$$U_{ni} = V_{ni} + \varepsilon_{ni}$$

The probability of individual n selecting alternative i is the probability her utility from i is greater than her utility from choosing any other available alternative:

Equation 7-2

$$\pi = Prob\left(V_{ni} + \varepsilon_{ni} \geq V_{nj} + \varepsilon_{nj}\right);\ \forall j \neq i$$

If we assume ϵ_{ni}'s are independently distributed Type-I extreme value errors and a linear utility function, such that $V_{ni} = x'_i\beta$, where x_i is a vector of attributes of i and β is a vector of parameters, then we can model the probability of individual n choosing alternative i as:

Equation 7-3

$$\pi_{ni} = \left(\frac{\exp(\mu_n x'_i\beta)}{\Sigma_{j=1}\exp(\mu_n x'_i\beta}\right)$$

where μ_n is a scale parameter commonly assumed to equal 1.

In this model, the coefficients are fixed, effectively assuming that all respondents have the same preferences (e.g., all respondents have the same value for a BEV, all else being equal). The logit model exhibits the independence of irrelevant alternatives (IIA), meaning that the odds of choosing vehicle j over vehicle k are independent of the choice set for all pairs j, k, which may imply unrealistic substitution patterns.

The first model we estimate that relaxes this assumption is a mixed logit. In the mixed logit model, developed by Train (1998), the coefficients of the utility function are random parameters for which we can specify a distribution. For example, if we assume a coefficient is normally distributed, we estimate both the mean and standard deviation of that coefficient. This model allows for heterogeneous preferences across respondents and does not necessarily exhibit the IIA property, thereby allowing for more flexible substitution patterns. Structurally, the mixed logit model is similar to the standard logit except the parameters of the utility function are assumed to be random, not fixed, and the probability of individual n selecting alternative i becomes:

Equation 7-4

$$\pi_{ni} = \int \frac{\exp(\mu_n x'_i \beta)}{\sum_{j=1}^{J} \exp(\mu_n x'_i \beta)} f(\beta|\theta) d\beta$$

where $f(\beta|\theta)$ is the density function of β.

A drawback of the mixed logit model is that it does not tell us where different respondents are in the estimated distribution of preferences.[38] In other words, it does not tell us which respondents have which preferences.

The alternative specific constant (ASC) logit and the latent class logit offer two different methods of further exploring heterogeneity. The ASC logit, developed by McFadden (1974), is a constant parameter logit where explanatory variables in the utility function include not only alternative attributes but also respondent characteristics. The ASC logit estimation therefore tells us how respondent characteristics impact their odds of selecting a BEV or PHEV relative to the gasoline version. The ASC logit is similar to the standard logit except the utility function includes consumer characteristics:

Equation 7-5

$$V_{ni} = x'_i \beta + z_n \gamma$$

where z_n is a vector of characteristics of individual n and γ is a vector of parameters.

The latent class model is similar to the ASC logit model in that preferences are heterogeneous across respondents' characteristics. The latent class model segments the population into different classes, where preferences for each class are estimated separately, and class membership of respondents is determined by their characteristics.

[38] Technically, it is possible to make the mean or variance of a mixed logit parameter a function of observed covariates, but in practice this is rarely done to problems because such models tend to be numerically unstable and frequently do not converge to a well-defined maximum value.

Assume existence of S segments in a population. The probability of consumer n choosing alternative i is conditional on membership in segment s, where $s = 1, . . , S$, is:

Equation 7-6

$$\pi_{ni|s} = \frac{\exp(x'_i \beta_s)}{\sum_{j=1}^{J} \exp(x'_j \beta_s)}$$

Allowing latent membership for segmentation to be:

Equation 7-7

$$M_{ns} = y'_n\lambda_s + \zeta_{ns}$$

where

M_{ns}: membership likelihood function for individual n to be in segment s

y_n: vector of both psychometric constructs and socioeconomic characteristics

λ_s: vectors of parameters

ζ_{ns}: independently distributed Type-I extreme value errors

we can model the probability of consumer n belonging to segment s as:

Equation 7-8

$$\pi_{ns} = \frac{\exp(y'_n\lambda_s)}{\sum_{s=1}^{S}(\exp(y'_n\lambda_s)}$$

The probability of consumer n choosing alternative i is the sum across segments of the probability of her selecting alternative i conditional on segment membership times her probability of segment membership:

Equation 7-9

$$\pi_{ni} = \sum_{s=1}^{S}\pi_{ns}\pi_{ni|s}$$

Equation 7-10

$$\pi_{ni} = \sum_{s=1}^{S}\frac{\exp(y'_n\lambda_s)}{\sum_{s=1}^{S}\exp(y'_n\lambda_s)}\frac{\exp(x'_i\beta_s)}{\sum_{j=1}^{J}\exp(x'_j\beta_s)}$$

7.4 Results

7.4.1 Mixed Logit Model

Table 7-3 shows the results of the mixed logit estimation. The first two columns are estimated assuming that the price coefficient is normally distributed. The second two columns assume the price coefficient is log normally distributed.[39] Specifications with log normally distributed price coefficients have a better model fit as shown by the pseudo-likelihood at the bottom of Table 7-3. This is unsurprising since the log normal distribution allows for the mean to be greater than the median, which might be the case if some respondents are very price sensitive. Table 7-3, below, shows that on average (and all else being equal), respondents have a negative preference for BEVs relative to conventional gasoline vehicles (the omitted category), a positive (relative) preference for PHEVs, a positive preference for increased range and HOV access, and a negative preference for higher refueling costs.

Table 7-3: Mixed Logit Results

	Price Normally Distributed		Price Log Normally Distributed	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Price ($1,000)	(-0.226***)	0.194**	(-2.520***)	0.397
	0.028	0.089	0.257	0.32
BEV	(-1.301**)	4.007***	(-1.605***)	4.348***
	0.656	0.95	0.46	0.817
PHEV	1.738**	2.745***	1.921***	2.423***
	0.772	0.461	0.407	0.428
Range	0.014***	0.004	0.017***	0.007***
	0.002	0.003	0.002	0.002
Refuel	(-0.158**)	0.057	(-0.128)	0.005
	0.072	1.095	0.096	0.24
HOV	0.311**	0.302	0.261***	0.400**
	0.128	0.753	0.087	0.159
Observations	24,940		24,940	
Log Pseudolikelihood	(-5,959)		(-5,931)	
Weighted to represent population of California new car buyers				
Robust standard errors in parentheses, clustered by respondent				
***p<0.01	**p<0.05	*p<0.1		

Figure 7-7 shows kernel density plots of respondents' estimated coefficients, using a sampling method from Revelt and Train (2000). The distribution of the (negative) price coefficient appears to be log normal, as shown in Figure 7-7a. The median price coefficient is around 0.3 and the mean is substantially higher, suggesting a sizable fraction of respondents are very price sensitive.

[39] A log-normal distribution assumption for a parameter implies the coefficient should be positive. Therefore, we transform price, multiplying it by -1 for the estimation, and transform the resulting positive coefficient back post-estimation, multiplying by -1. Therefore, the price coefficient for the log-normal specification shown in Table 4-3 is negative.

Figure 7-7b shows that the distribution of coefficients for BEVs is bi- or perhaps even trimodal. While most respondents have a negative coefficient for BEVs of around -2, a small portion of the population has a positive preference for BEVs, and a significant portion of the population has an even stronger dislike of BEVs. Similarly, Figure 7-7c shows that the distribution of coefficients for PHEVs is bi-modal, with a minority of respondents having a coefficient around -2, but a majority of respondents having a strong positive preference for PHEVs with a coefficient closer to 4.

While range has a positive coefficient for all respondents, the distribution of the range coefficient as shown in Figure 7-7b also exhibits bi-modality, with some respondents caring significantly more than others, perhaps due to different commute distances.

Figure 7-7e shows that a minority of respondents does not seem to care about refueling costs, with a coefficient of zero, but that a majority of respondents do care about refueling costs, with a coefficient around -2. Similarly, Figure 7-7f shows that a large majority of respondents value HOV lane access, but a minority does not, which may reflect a lack of local HOV lane access.

Figure 7-7: Mixed Logit Coefficient Distributions

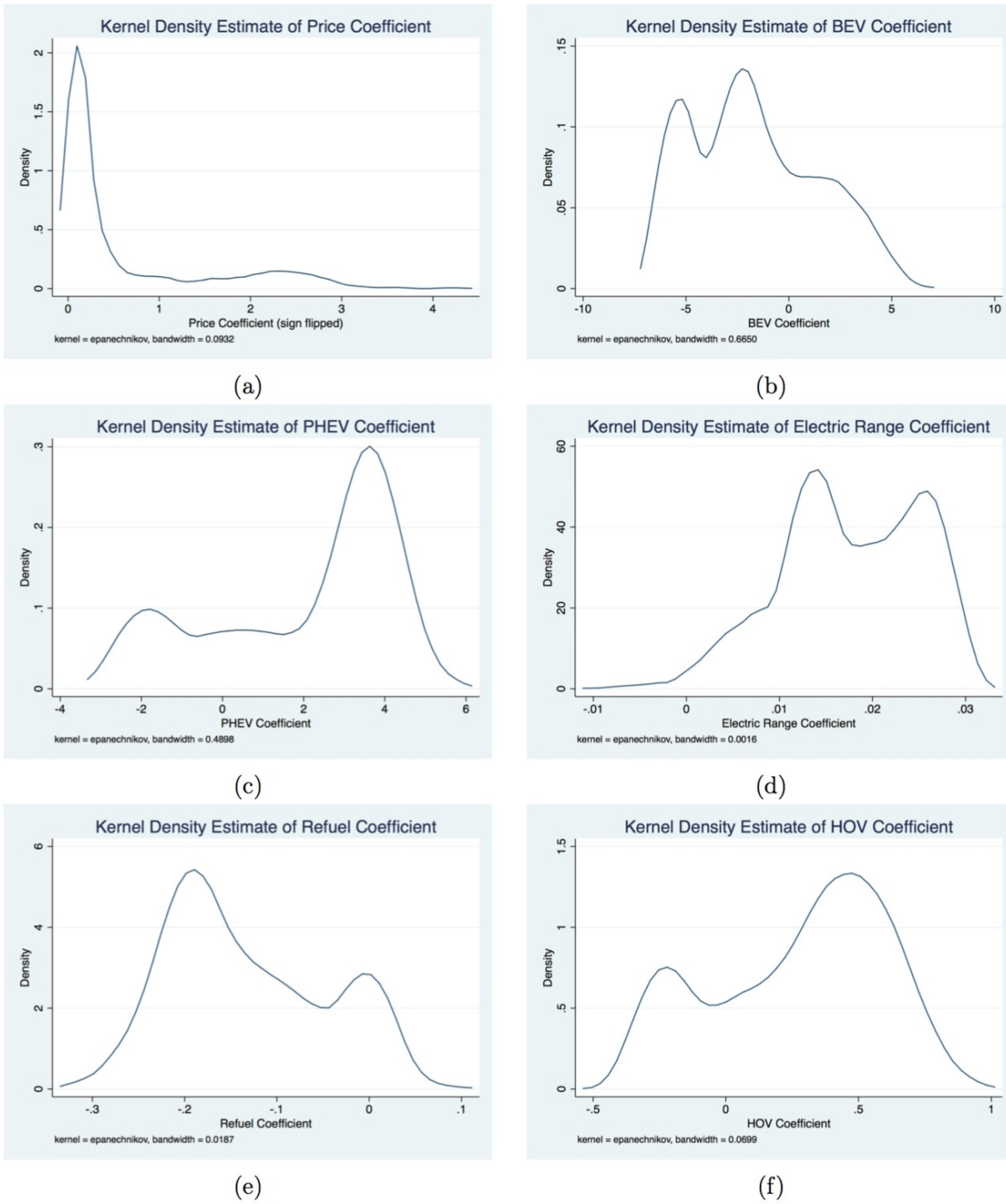


Table 7-4, below, shows the mean estimates of willingness to pay (WTP) for vehicle attributes obtained using the Hensher and Greene approach (Hensher and Greene, 2003).[40]

Table 7-4: Willingness to Pay

	WTP (Price Normally Distributed)	WTP (Price Log Normally Distributed)
BEV	(-$18,693)	(-$4,906)
PHEV	$12,873	$6,783
Additional Mile of Electric Range	$81	$57
Additional $ per Gal Refuel Cost	(-$874)	(-$430)

We find that the sample's average WTP for a BEV is about -$4,900. Out of BEVs on the market as of late 2013 or early 2014 that have a comparable internal combustion engine (ICE) vehicle model, the BEVs were priced at an average premium of $18,411 (see Table 7-5 for details). We find that the sample's average WTP for a PHEV is nearly $6,800. Out of PHEVs on the market as of early 2014 that have a comparable ICE model, the PHEVs are priced at an average premium of $11,024 (see Table 7-5 for details). This suggests that the gap between WTP and the price premium for BEVs is very high, on the order of $23,000, while the gap between WTP and the price premium for PHEVs is much smaller, on the order of $4,000. State level incentives are typically a few thousand dollars, and the federal income tax incentive is up to $7,500. This suggests that current financial incentives will stimulate fewer BEV purchases, but could stimulate more PHEV purchases. This is consistent with the results that we present in the next chapter finding that California's PEV rebate policy induces more marginal PHEV purchases than marginal BEV purchases.

[40] To calculate the mean WTP for each attribute, we took the mean of 10,000 random draws from the distribution of the attribute's coefficient divided by the exponential of a random draw from the distribution of the price coefficient. These simulations are based on consumers' responses and the resulting estimated model coefficients.

Table 7-5: Price Comparison of Internal Combustion Engine (ICE) vehicles and PEVs of the Same Model [41]

	ICE MSRP	BEV MSRP	Premium
Smart for Two	$13,270	$25,000	$11,730
Chevrolet Spark	$12,170	$26,685	$14,515
Ford Focus	$16,810	$35,170	$18,360
Toyota RAV4	$23,550	$49,800	$26,250
Honda Fit	$15,425	$36,625	$21,200
Avg Premium			$18,411
Ford C-Max	$25,170	$32,920	$7,750
Ford Fusion	$21,970	$34,700	$12,730
Honda Accord	$21,955	$39,780	$17,825
Toyota Prius Plug-In	$24,200	$29,990	$5,790
Avg Premium			$11,024

Source: MSRPs are taken from auto makers' websites and www.edmunds.com. MSRPs as of March 2014.

It should be noted that state and federal incentives were not included in the survey PEV price. The average survey respondent would pay approximately $589 per year on refueling costs per $1 increase in $/gal equivalent. This is based on the assumption that the respondent refuels once every week and a half, and that the respondent's fuel tank capacity is 17 gallons. These are the average values based on the survey responses. Thus, the WTP for refuel savings of $1 per gallon of $430 implies a high discount rate, with an expected payback period of just under one year. We find that the average respondent is willing to pay about $900 when purchasing a PEV for the associated free single-occupant HOV lane access. Bento et al. (2014) estimate the average annual rent of a hybrid HOV sticker in southern California to be $743, with a net present value of $4,800. Shewmake and Jarvis (2014) estimate an average premium of $3,200 for a hybrid with an HOV sticker, which translates into a yearly value of $625.

The mixed logit results show that there is considerable heterogeneity in preferences across BEVs and PHEVs, as well as across consumers. Sections 7.4.2 and 7.4.3 attempt to better understand the underlying sources of this heterogeneity.

7.4.2 Alternative-Specific Constant Logit Model

Tables 7-6 and 7-7 show the results of the ASC logit estimation. As shown in Table 7-6 to allow for non-linear effects of vehicle range on utility, the variable range also enters this model as a squared term. The coefficient on price in Table 7-6, -.06, is smaller in absolute value than the -2.5 estimated by the preferred specification in Table 7-3. The former estimate assumes the coefficient is fixed, while the latter estimate assumes the coefficient follows a log normal distribution and allows for the mean to be greater than the median, which might be the case due to a small fraction of respondents being very price sensitive. The coefficients on refueling costs and HOV access are similar between Tables 7-3 and 7-6. The BEV and PHEV coefficients

[41] The effectiveness of the choice set design does not rely upon the actual level of BEV and PHEV prices.

are not directly comparable, as those in Table 7-6 must be adjusted by respondent characteristics as shown in Table 7-7.[42]

Table 7-6: Alternative-Specific Constant Logit, Main Results

Price ($1,000s)	(-0.062***)
	0.009
BEV	(-9.701***)
	3.604
PHEV	(-8.936***)
	2.701
Range	0.033***
	0.003
$Range^2$	(-0.0001***)
	0.00001
Refuel	(-0.086**)
	0.045
HOV	0.239***
	0.057
Observations	24,620
Log Pseudolikelihood	(-6,732)
***p<0.01 **p<0.05 *p<0.1	

Weighted to represent population of California new car buyers
Robust standard errors in parentheses, clustered by respondent

[42] For example, the coefficient on Gasoline Price in Table 4-7 is approximately 1.5, and the gasoline price in most census tracts during December of 2013 was greater than $3, such that at least 3x1.5 = 4.5 must be added to both the BEV and PHEV coefficients in Table 4-6.

Table 7-7: Alternative-Specific Constant Logit, ASC Results

	BEV	PHEV
Small Body	(-0.126)	(-0.014)
	0.21	0.196
Household Vehicles	0.091	0.196*
	0.122	0.112
Outlet	0.367	0.394*
	0.237	0.214
Parking at Work	1.967***	0.809
	0.627	0.566
Commute under 20mi	(-0.803**)	(-0.681***)
	0.316	0.263
Use Gas Mode Daily	(-1.302***)	(-1.243***)
	0.364	0.283
HOV Access	0.123	0.456***
	0.161	0.135
Pro Environment	0.886***	0.427**
	0.215	0.195
Early Adopter	0.207***	0.130***
	0.055	0.05
Charging Station Densit	0.004	0.01
	0.02	0.02
Gas Price	1.598	1.795**
	0.979	0.714
Low Income (<$30k)	(-0.228)	0.148
	0.354	0.315
High Income (>$100k)	(-0.415*)	(-0.070)
	0.233	0.206
Observations	24,620	24,620
Log Pseudolikelihood	(-6,732)	(-6,732)

Weighted to represent population of California new car buyers
Robust standard errors in parentheses, clustered by respondent

We are able to achieve convergence in the ASC logit estimation when a quadratic range term is included. When we include this term, we get more precision on the refueling cost coefficient. In Table 7-6, focusing on the range variable, we find that consumers' utility for range exhibits decreasing returns; that is consumers value an increase range of 10 miles when it extends vehicle range from 10 to 20 miles more than when it extends vehicle range from 160 to 170. This is consistent with the literature (Bunch et al., 1993; Brownstone, Bunch, and Train, 2000). The linear and quadratic range coefficients suggest an optimal electric range of 165 miles for BEVs.

Table 7-6 shows that all else being equal, consumers prefer PHEVs to BEVs by a narrow margin. Table 7-7 shows that having pro-environment preferences and self-identifying as an early adopter increase a respondent's WTP for both BEVs and PHEVs, although relatively more for BEVs.

Respondents with round-trip commutes under 20 miles are less likely to select PEVs. This may be because a shorter commute would accrue less refueling cost savings, making it more difficult for the consumer to justify the higher upfront cost of a PEV.

The environmental benefits associated with driving a PHEV depend on the relative number of miles driven in electric versus gasoline mode. While the California Air Resources Board assigns higher rebates to BEVs with the belief that they are associated with greater environmental benefits than PHEVs, it is sometimes argued that PHEVs may result in close to the same environmental benefits if daily commuting can be done in all-electric mode (California Environmental Protection Agency, 2007). PHEVs do not invoke range anxiety or impair the ability to take longer occasional trips. The results in Table 7-7 support this assertion. Respondents who anticipate needing to use "gasoline mode" on a daily basis if they owned a PHEV are much less likely to purchase either a BEV or a PHEV. This effect is similar for BEVs and PHEVs, suggesting prospective PHEV drivers are equally as motivated to commute primarily in all-electric mode, even though they do not face the same total range constraints as BEVs.

The positive coefficients on charging outlet access in Table 7-7 suggest that respondents who have an electrical outlet near their home parking spot are more likely to purchase a PEV. This is consistent with earlier studies (Axsen and Kurani, 2009; Hidrue et al., 2011). Notably, outlet access appears just as important for PHEVs as BEVs, even though PHEVs do not require the electric battery be charged in order to drive the vehicle in gasoline mode. However, when we replace the outlet variable with an indicator variable for whether the respondent lives in a single-family house, this coefficient is positive and statistically significant at the 10% level for BEVs but smaller and not statistically different from zero for PHEVs.[43] This may suggest that BEV owners are more comfortable plugging into an outlet at their single family residence while PHEV owners living in multifamily housing are also comfortable plugging into a less private or less exclusive outlet near their residential parking spot.

The coefficient on the indicator for whether a respondent parks in a garage while at work is positive and highly statistically significant for BEVs but smaller and not significant for PHEVs. Respondents with access to a parking garage at work may anticipate a higher likelihood of charging access while at work, which would increase their utility for all types of PEVs. These coefficients suggest that workplace charging is a more important issue for BEV adoption than

[43] If we substitute the Outlet variable with Single House, the BEV coefficient on Single House is 0.427* (0.234) and the PHEV coefficient on Single House is 0.151 (0.207), with other coefficients not significantly different. We do not include Outlet and Single House in the same specification due to concerns about collinearity.

PHEV adoption. The coefficients on public charging station density are positive but not statistically different from zero.

The coefficients on HOV lane access are positive, but that for BEVs is smaller than that for PHEVs and not statistically significant. This suggests that new car buyers who live near HOV lanes are more likely to purchase PHEVs, and that government policies allowing free single-occupant HOV lane access increases a consumer's probability of purchasing a PHEV. As we showed in Chapter 6, California's HOV lane policy had a positive impact on both BEV and PHEV adoption, with relatively more impact on the PHEV market.

The coefficient on number of household vehicles is positive for both vehicle types, although only statistically significantly greater than zero for PHEVs. This lends support to the "Hybrid Household" hypothesis that households with larger vehicle fleets are more likely to diversify their vehicle holdings with alternative vehicles (Kurani, Turrentine, and Sperling, 1996).

Although the majority of PEVs on the market have historically been smaller vehicles, this result is unsurprising because in our choice experiment, respondents were allowed to choose PEV versions of any body type. Again we designed this study to be able to characterize consumer choices for the future emerging market, which will contain a much greater range of models.

7.4.3 Latent Class Logit Model

Tables 7-8 and 7-9 show the results of a latent class estimation assuming three segments, using a variety of sociodemographic variables and attitudes to determine segment membership. Note that the latent class groups are helpful in explaining the kernel density estimate of coefficients. For example, Figure 7-7B shows that there are three peaks in the BEV coefficient distribution: one at a large negative number, the biggest at a small negative number, and the third and smallest peak at a near-zero positive number. These three peaks are consistent with the three BEV preferences of the different segments.

Table 7-8: Latent Class Model: Segment Preferences

	Segment 1	Segment 2	Segment 3
Price ($1,000s)	(-0.193***)	(-0.387***)	(-0.024***)
	0.016	0.052	0.007
BEV	(-3.757***)	(-3.031***)	(-0.197)
	0.382	0.485	0.3
PHEV	0.643**	(-1.531***)	0.511**
	0.298	0.403	0.251
Range	0.051***	0.013**	0.018***
	0.003	0.006	0.003
Range	(-0.0002***)	(-0.00003)	(-0.00003***)
	0.00002	0.00002	0.00001
Refuel	(-0.219***)	(-0.088)	(-0.123**)
	0.073	0.105	0.052
HOV	0.382***	(-0.073)	0.232***
	0.089	0.156	0.064
Class Share	42.4%	26.1%	31.5%
Observations	24,940	24,940	24,940
Standard errors in parentheses			
***p<0.01	**p<0.05	*p<0.1	

Table 7-9: Latent Class Model: Segment Membership

	Segment 1	Segment 2	Segment 3†
Household Size	(-0.049)	(-0.238***)	0.000
	0.07	0.077	0.000
Household Vehicles	0.231***	0.172	0.000
	0.106	0.113	0.000
Age under 35	-0.648***	(-0.305)	0.000
	0.205	0.217	0.000
Age over 60	0.548**	0.504*	0.000
	0.255	0.258	0.000
Low Income (<$30k)	0.322	0.108	0.000
	0.262	0.267	0.000
High Income (>$100k)	0.349*	0.074	0.000
	0.211	0.225	0.000
College Education	0.056	(-0.290)	0.000
	0.187	0.197	0.000
Use Gas Mode Daily	0.005	0.793**	0.000
	0.382	0.357	0.000
Single House	(-0.398**)	(-0.313)	0.000
	0.194	0.204	0.000
HOV Access	0.05	(-0.436***)	0.000
	0.121	0.133	0.000
Pro Environment	(-0.641***)	(-1.088***)	0.000
	0.175	0.191	0.000
Early Adopter	(-0.077*)	(-0.219***)	0.000
	0.046	0.049	0.000
Liberal	0.332*	(-0.017)	0.000
	0.189	0.212	0.000
Constant	0.277	1.439***	0.000
	0.405	0.407	0.000
Class Share	42.4%	26.1%	31.5%
Observations	24,940	24,940	24,940

Standard errors in parentheses

***p<0.01 **p<0.05 *p<0.1

†Segment 3 is the baseline segment that the other segments are compared to.

Table 7-8 shows consumer Segment 3 has a positive WTP for PHEVs and a WTP for BEVs that is approximately zero. This class is by far the most receptive to BEVs. Table 7-9 shows that environmentalists and early adopters are more likely to be in Segment 3. Consumers who reside in single-family houses and younger consumers are also more likely to be in Segment 3. These findings support the notion that demand for BEVs is driven by strong environmental preferences and eagerness to adopt new technologies. These findings also confirm earlier results that households with home charging infrastructure are relatively more likely to purchase PEVs.

Table 7-8 shows consumer Segment 2 has a negative WTP for both BEVs and PHEVs. This is also the most price sensitive segment. Segment 2 has less strong preferences for range and is indifferent towards refueling cost and HOV lane access, perhaps as a result of their low likelihood of selecting a PEV. The results in Table 7-9 show that consumers who are less educated, more conservative, less concerned about the environment, and tend not to be early adopters are more likely to belong to this segment.

Consumer Segments 2 and 3 are consistent with there being a group of consumers which is enthusiastic about PEVs and another class that will have nothing to do with PEVs. Consumer Segment 1 is the most interesting, because this segment has more nuanced preferences and also represents the largest of the three segments. Table 7-8 shows consumer Segment 1 has a negative WTP for BEVs but a positive WTP for PHEVs. They are more price sensitive than Segment 3.

Consumers who have HOV lane access, who do not live in single-family houses, and who are more liberal are more likely to belong to Segment 1, as shown in Table 7-9. Respondents fitting this profile tend to live in urban areas. Additionally, consumers who are older, have higher incomes, and are more educated are more likely to belong to Segment 1. This segment's positive preference for PHEVs appears to stem not from environmental or early adopter preferences but rather from more pragmatic reasons such as refueling cost savings and HOV lane access. This segment's negative preference for BEVs may be in part driven by less access to home charging.

The latent class results show that the BEV market may be constrained since less than a third of the new car buying population seems willing to consider purchasing a BEV, all else being equal. A much larger fraction of the population, and one that breaks out of the early adopter/environmentalist niche, seems willing to consider purchasing a PHEV.

7.5 Implications for Policy and the Emerging Market

In the ASC logit model we find that consumers' utility for range exhibits decreasing returns. The linear and quadratic range coefficients suggest an optimal electric range of 165 miles. A similar calculation for the latent class model suggests optimal ranges for Segment 1, 2 and 3 of 127.5, 216.7, and 300 miles, respectively. Segment 3 is the most likely to choose a BEV and is the least price sensitive, so it makes sense this segment is willing to pay for a longer range. Segment 1 is more likely to purchase a PHEV, such that a more cost-effective, shorter range vehicle may be sufficient.

In the mixed logit model, we find that the average respondent is willing to pay a one-time purchase premium of about $900 for free single- occupant HOV lane access. In the ASC logit model, the coefficients on HOV lane access are positive, but that for BEVs is smaller than that for PHEVs and not statistically significant. This suggests that new car buyers who live near HOV lanes are more likely to purchase PHEVs, and that government policies allowing free single-occupant HOV lane access increase the consumer probability of purchasing PHEVs.

In the ASC logit model we find that charging close to home (e.g. residential charging) access appears just as important for PHEVs as BEVs, even though PHEVs do not require the electric battery to be charged in order to drive the vehicle in gasoline mode. These results suggest that home charging is just as important to consumers considering a PHEV purchase. Our latent class model similarly suggests that consumers living in a single-family household are more likely to purchase BEVs. In the ASC logit model we also find evidence that the ability to charge at work is more important for BEV adoption than PHEV adoption.

The latent class model reveals three distinct consumer segments. About a quarter of the new car buyer population seems to be less urban, more conservative, and have strong negative preferences for all PEVs. A third of the population has pro-environmental preferences and a tendency for early adoption. This is the only segment that does not have a strong negative preference for BEVs. The last segment, Segment 1, tends to be more suburban, older, higher income, and more educated. These consumers have a strong negative preference for BEVs but a strong positive preference for PHEVs. This positive preference for PHEVs appears not to stem from environmental or early adopter preferences. This segment's negative preference for BEVs may be in part driven by less access to home charging.

The latent class results show that the BEV market is not constrained since almost a third of new car buyers are willing to purchase a BEV. On the other hand, a much larger and more general population seems more willing to consider purchasing a PHEV and even has a positive willingness to pay for this technology relative to a conventional gasoline vehicle. This suggests that the addition of PHEVs to the market may stimulate PEV demand in consumer segments who would otherwise be unlikely to purchase a BEV. These findings also imply that many PHEV purchasers would not purchase a BEV, and such sales would represent growth in the overall PEV market rather than cannibalization of the BEV market. We speculate that due to the strong negative preferences for BEVs in most of the population and cost differentials that are large relative to subsidy levels being considered by policy makers, much of the future growth of the PEV market will be driven by demand for PHEVs from Segment 1.

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Chapter 8: Designing Policy Incentives for Cleaner Technologies—Lessons from California's Rebate Program

The State of California offers a rebate of $1,500 for PHEVs and $2,500 for BEVs. In this chapter we explore whether, and how by much, the presence of these rebates has increased the sale of BEVs and PHEVs. We also explore several alternative rebate designs. We explore the effectiveness of new designs which give progressively higher rebates to lower income. This analysis responds to state legislation (SB 1275 and SB 535) which has sought to understand and improve the equity impacts of rebate programs for different consumers with different income levels.

We use California's Clean Vehicle Rebate Project as a reference case in order to explore the opportunity for both more cost-effective and equitable policy designs. In our policy setting, there are several possible sources of heterogeneity that the incentive policy's design might leverage. First, the policy may set different rebate levels for different products, in our case for battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). Second, a policy may employ price caps, which would make PEVs above the specified price ineligible for a rebate. Third, a policy could base rebate levels on heterogeneity among consumers.

Recently, California adopted legislation (SB 1275) requiring rebate levels to vary with consumers' income levels but not specifying how rebate levels should vary. ARB approved the Fiscal Year 2015-16 Low Carbon Transportation Investments and AQIP Funding Plan in late June 2015, which included changes to CVRP: Income cap for higher-income consumers and increased rebate levels for low- and moderate-income consumers. The income eligibility changes applied to rebate applications for vehicles purchased or leased on or after the implementation date of March 29, 2016. For low- and moderate-income consumers, CVRP rebates for all types of eligible light-duty passenger vehicles increased by $1,500. Higher income consumers are no longer eligible for CVRP rebates if their gross annual income exceeds $250,000 for single tax filers, $340,000 for head of household filers and $500,000 for joint filers. Income levels were determined by the amount reported on the applicant's federal tax return. [44]

We develop a theoretical model of a social planner who must determine the rebate level to assign to consumers in order to maximize PEV purchases subject to a budget constraint. Our

[44] Sources: 1) California Clean Vehicle Rebate Project Income Eligibility: https://cleanvehiclerebate.org/eng/income-eligibility
2) Center for Sustainable Energy: "CVRP Initiates New Eligibility Requirements March 29, 2016" https://energycenter.org/article/cvrp-initiates-new-eligibility-requirements-march-29-2016

social planner faces heterogeneous consumers in their ex ante utilities for the new products, their marginal utilities of income, and the impact that a knowledge spillover has on the purchase of the new technology. Our model predicts that the social planner's optimal rebate decreases as a consumer's ex ante value of the product increases. Consumer segments with high ex ante values for the product are more likely to purchase the product under any policy, thus qualifying in greater numbers for the rebate than are consumer segments with lower ex ante product values. As a result, targeting consumers with lower ex ante values may be more cost-effective, requiring less public rebate revenue for the same change in consumer probabilities of product switching. Second, our model predicts that the social planner's optimal rebate value increases as the consumer's own marginal utility of income increases. Any given rebate level is more effective in maximizing the sum of probabilities of purchasing the product for the segment of consumers who are relatively more price responsive.

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

To evaluate the effects of a variety of rebate designs, we first develop and estimate an innovative empirical model of consumer vehicle choice. The centerpiece of our empirical analysis is a consumer vehicle choice model that enables us to model the consumer choices across all makes and models in the California market. A statewide representative survey of 1,261 new car buyers in California enables us to identify individual preferences for conventional and alternative vehicle technology attributes, allowing us to estimate price elasticities of demand and willingness to pay for different vehicles. We integrate this data on vehicle sales and market structure to predict the effect of alternative rebate policy designs on our policy performance metrics.

We then use this model to simulate the performance of rebate designs. We find that baseline rebate levels ($1,500 for PHEVs and $2,500 for BEVs) are effective, increasing the virtual market share of PEVs by at least 7%. Taking into account the estimated incidence of "free riding" by consumers who would have purchased PEVs in the absence of rebates, the policy cost per induced PEV purchase is around $30,000 for the baseline policy.

Our initial simulation of alternative policy designs explores the effects of changing rebate levels across the two vehicle technologies (BEVs and PHEVs). We simulate the impacts of consumers' differing ex ante values (e.g., willingness to pay) for BEVs and PHEVs on the performance of rebate policies. For example, allocating higher rebates to BEVs, which survey respondents valued less highly than PHEVs, reduces the number of total additional PHEVs sold, but also improves policy cost-effectiveness and lowers total policy costs. While some observers would offer BEV purchasers higher rebates because they believe BEVs produce higher social benefits, our recommendations that BEV buyers receive higher rebates than PHEV buyers is based solely upon a policy cost-effectiveness criteria.

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

Our third set of analyses evaluates redesigning the existing rebate program to give consumers in lower-income classes relatively higher rebates. Rebate policy designs that are progressive with respect to income reduce the number of consumers receiving rebates who would have purchased PEVs anyway. These policies also target lower-income consumers who have a higher marginal value for the rebate and who are less likely to purchase a PEV without higher rebates. We find that these policies increase the number of additional PEVs sold per rebate dollar spent (i.e., the cost- effectiveness of the policy) relative to the baseline policy.

Overall simulation results for two types of policy designs are superior to simulation results for California's baseline policy along performance dimensions. The first type of policy offers very progressive rebate levels based on consumer income levels. An example of this policy would offer consumers purchasing BEVs who make incomes of 1) less than $25,000, a rebate of $7,500, 2) $25,000- $50,000, a rebate of $5,000, 3) $50,000-$75,000, a rebate of $2,000, and 4) over $75,000, no rebate. Consumers purchasing a PHEV in these same income categories would receive $4,500, $3,000, $1,000, and no rebate respectively. The second policy combines a less progressive rebate schedule with a vehicle price cap. An example of this policy would implement a $60,000 vehicle price cap above which no rebate is offered while offering consumers making less than $100,000 a rebate of $5,000 for BEVs and $3,000 for PHEVs. These policies are projected to sell at least as many additional PEVs over the next three years as the baseline policy, are more cost-effective (e.g., PEV sold per dollar spent), have lower total policy costs, and result in significantly greater allocative equity.

8.2 Theoretical Model

A utility-maximizing individual will purchase a vehicle when her utility from doing so exceeds her utility from purchasing any other available vehicle as well as her utility from not purchasing a vehicle. In this chapter we focus on the decision to purchase a new PEV, contingent upon having chosen to purchase a new vehicle. This reflects the data constraints of our study, which uses survey data from a sample of new car buyers who intend to purchase a new vehicle in the next few years.[45]

Contingent upon having decided to purchase a new vehicle, an individual purchases a PEV when her total utility from the decision, $u_{i,PEV}$, is greater than her utility for purchasing any other vehicle, u.[46] Let total, minus the cost of the PEV, p, times her marginal utility for the PEV be her ex ante value for the PEV, v_i utility of income, i. The social planner reduces PEV price for consumers by assigning rebates, r_i, out of a policy budget, R, such that

Equation 8-1

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

The policy maker's objective is to maximize the sum of new car buyer probabilities of purchasing PEVs by allocating the rebates cost effectively subject to the budget constraint:

Equation 8-2

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

Equation 8-3

$$S.T. \sum_i E[\pi_i r_i] \leq R$$

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

Equation 8-4

$$max_{r_i} \sum_i \frac{\exp(u_{i,PEV})}{\sum_K (u_{i,PEV})} = max_{r_i} \sum_i \frac{\exp(v_i - \beta_i(p - r_i))}{\exp(v_i - \beta_i(p - r_i)) + \sum_j \exp(u_{i,j})} \forall j \neq PEV$$

[45] For further discussion, see Sections 7.4.1 and 7.4.2

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

The choice variable is the rebate level, r_i, which only affects utility of the PEV and not the utility of other vehicles. The social planner cannot affect the utility of the other vehicles (ui,j for j ? PEV). Therefore, in this framework, maximizing the sum of the probabilities of choosing the PEV is equivalent to maximizing the sum of the utilities for the PEV:[47]

Equation 8-5

$$max(r_i)\sum_i [v_i - \beta_i(p - r_i)]$$

$$S.T.\sum_i E\,[\pi_i r_i] \leq R$$

Where $\pi_i$is the probability that consumer i selects a PEV. Solving the constrained maximization problem above results in the following first order condition, where λ is the shadow value of the budget constraint:

Equation 8-6

$$\lambda = \frac{\beta_i}{\pi_i}$$

If there are N new car buyers, then there are N first order conditions similar to Equation 7-6, one for each car buyer. We can solve these first order conditions for λ and set them equal to each other. The stylized case where $N = 2$ is instructive because it can help illustrate the influences of varying the characteristics of two different consumers. In this analysis the reader may think of *own* values as those of consumer 1 with reference to one *other* consumer that we will call consumer 2. In this context, we find the following:

Equation 8-7

$$\frac{\beta_1}{\pi_1} = \frac{\beta_2}{\pi_2}$$

The probability of selecting a PEV, π_i is proportional to the utility of selecting the PEV, $v_i - \beta_i p + \beta_i r_i$. As such, we find the following comparative statics:

Optimal rebate decreases as own ex ante value increases:

Equation 8-8

$$\frac{dr_1}{dv_1} < 0$$

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

Optimal rebate increases as other's ex ante value increases:

$$\frac{dr_1}{dv_1} > 0$$

Equation 8-9

$$\frac{dr_1}{dv_2} > 0$$

Optimal rebate increases as own marginal utility of income increases:

Equation 8-10

$$\frac{dr_1}{d\beta_1} > 0$$

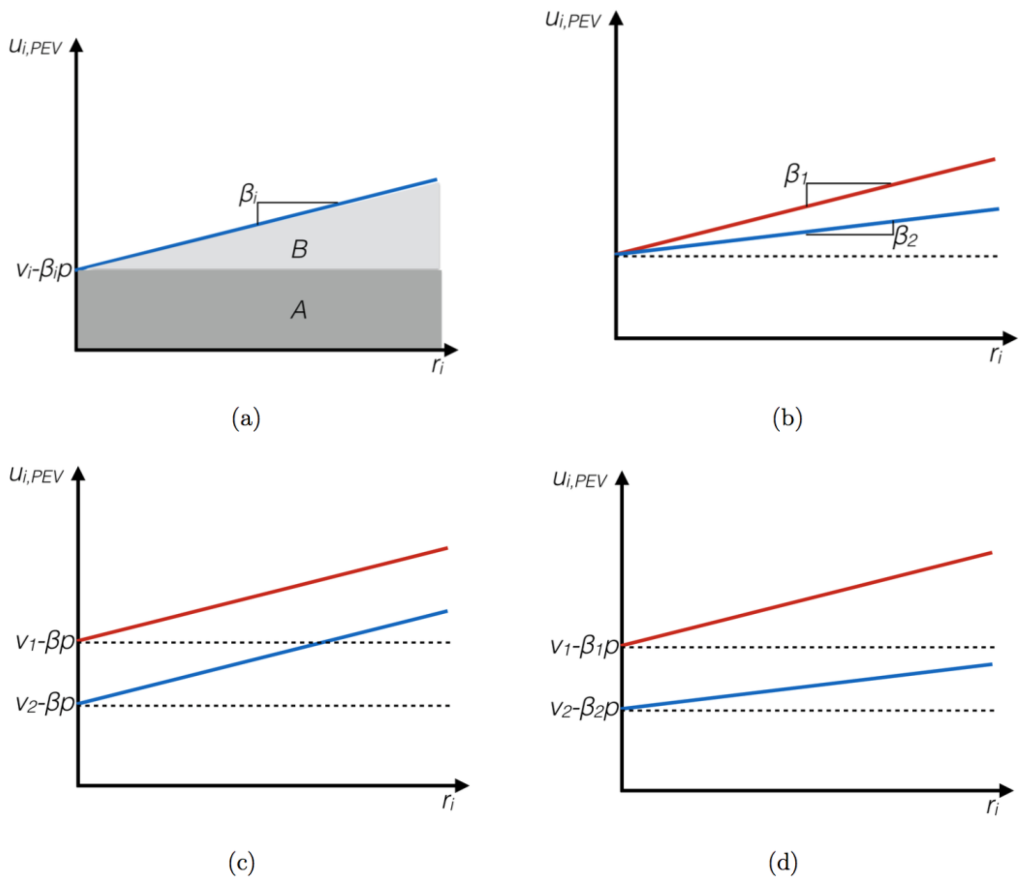
Optimal rebate decreases as other's marginal utility of income increases.

Equation 8-11

$$\frac{dr_1}{d\beta_2} < 0$$

Our comparative statics show that higher rebates should be assigned to consumers with higher marginal utility of income and/or lower ex ante value for PEVs. The intuition for this result is shown below in Figure 8-1.

Figure 8-1: Marginal versus Non-Marginal PEV Purchase Probability



Probability of purchasing the PEV is proportional to utility for the PEV. As shown above in Figure 8-1a, we can plot utility of the PEV versus rebate level as a linear function where the y-intercept is utility without the rebate, $v_i - \beta_i p$, and the slope of the function is the marginal utility of income, β_i. Although probability of purchasing the PEV increases with r_i, there is positive probability that the consumer will purchase the PEV in the absence of the rebate. If the consumer purchases the PEV in the absence of the rebate, the purchase is non-marginal in the sense that the purchase was not induced by the rebate policy. Area A is a proxy for the non-marginal purchase probability. Area B is a proxy for the marginal purchase probability; that is, by how much the rebate increases the probability of the consumer purchasing a PEV. The higher the consumer's ex ante value for PEVs, the higher her non-marginal purchase probability. The higher the consumer's marginal utility of income, the more responsive she will be to the rebate, and the higher her marginal purchase probability. The comparative statistics show us that rebates are more cost effective when they target consumers with a higher ratio of marginal to non-marginal purchase probability, i.e., lower ex ante values and higher marginal utilities of income.

Figure 8-1b shows that if two consumers have the same probability of purchasing the PEV in the absence of the rebate, the policy maker should target the rebate towards consumer 1, who has the higher marginal utility of income and thus has a higher ratio of marginal to non-marginal purchase probability. Figure 8-1c shows that if two consumers have the same marginal utility of income, the policy maker should target the rebate towards consumer 2, who has the lower ex ante value and thus has a higher ratio of marginal to non-marginal purchase probability. In Figure 8-1d consumer 1 has a higher ex ante value for the PEV and a higher marginal utility of income, whereas consumer 2 has a lower ex ante value and a lower marginal utility of income. In this case the policy maker would want to assign rebates r1 and r2 such that the ratio of consumer 1's marginal purchase probability to non-marginal purchase probability equals that of consumer 2, as proscribed by Equation 8-7.

We can also think about Figure 8-1 as a demand curve, since PEV utility on the y-axis is proportional to quantity demanded and rebate on the x-axis is a measure of price. Therefore, our theoretical results suggest that rebates should be targeted towards consumer segments with lower market share and steeper demand curves. Targeting consumer segments and/or products with lower market share is cost effective because it results in fewer rebates being allocated to infra-marginal purchases. Targeting consumer segments and/or products with steeper demand curves is more cost effective because the rebates stimulate more marginal purchases.

8.2.1 Cost-effectiveness Analysis of Rebate Designs Across two Technologies

In our empirical analysis, we will limit ourselves to a cost-effectiveness analysis of alternative rebate designs rather than evaluating the socially optimal rebate design. We do not know the marginal social benefits (e.g., avoided externalities) associated with PEV purchases which would be needed to define a social optimum. However, the social planner's problem above makes several predictions (e.g., Equations 8-8, 8-9, 8-10, and 8-11) about how to improve the cost-effectiveness of rebate policy designs with information readily available to the economists' standard demand analyses.

We will adapt and apply this model prediction to our empirical and simulation setting to increase the number of additional PEV purchases induced per public dollar spent (e.g., cost-effectiveness). We will consider the policy problem of setting rebate levels for two types of PEVs, BEVs and PHEVs, for which consumers have different ex ante values. Consumers' ex ante values are lower for BEVs than PHEVs. From Equation 8-8, we predict that if rebate levels are relatively higher for BEVs than for PHEVs then the policy will be relatively more cost-effective. We also consider the policy problem of setting rebate levels when the marginal utility of income varies across consumer (e.g., income) classes. We find that lower-income classes have a higher marginal utility of income than do higher-income classes. Equation 8-10 suggests that relatively higher rebate levels for relatively lower-income classes will produce relatively more cost-effective policy outcomes.

8.3 Empirical Model and Simulations

8.3.1 Empirical Model

The probability of a new car buyer selecting vehicle k can be described as the new car buyer population-weighted average of the probabilities of new car buyers selecting vehicle k:

Equation 8-12

$$Prob(V_k) = \frac{\sum_{i=0}^{N} w_i Prob_i(V_k)}{\sum_{i=0}^{N} w_i}$$

where

$Prob(V_k)$: Average probability of purchasing vehicle k

$Prob_i(V_k)$: Probability of individual i purchasing vehicle k

w_i: Weight on individual i needed to make the sample representative of the new car buying population

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

Equation 8-13

$$Prob_i(V_k) = Prob_i(Vehicle) Prob_i(New\ Vehicle|Vehicle) Prob_i(M_k) Prob_i(B_k) Prob_i(V_k|M_k, B_k)$$

where

M_k: Make of vehicle k

B_k: Body type of vehicle k

The survey focuses on individuals who have already decided to purchase a new vehicle. We model the decision to purchase a PEV contingent upon having decided to purchase a new vehicle:[48]

[48] This truncated model assumes that all households planning to purchase a new vehicle follow through with their decision, and that no households not planning to purchase a new vehicle change their minds. There are a few potential violations of this assumption. There may be households who intend to purchase a new vehicle but do not because their current vehicle lasts longer than expected or due to adverse financial shocks. There may be households who were screened out of our sample due to their stated intention not to purchase a new vehicle who

Equation 8-14

$$Prob_i(V_k|NewVehicle) = Prob_i(M_k)Prob_i(B_k)Prob_i(V_k|M_k, B_k)$$

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

Equation 8-15

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

Equation 8-16

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

Equation 8-17

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

where

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

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

8.3.2 Data

For this analysis we use the same survey data as in chapter 7. Please see that chapter for a detailed discussion our survey design and methods. Also see Chapter 7 for basic description of the survey results.

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nevertheless purchase a new vehicle because their current vehicle breaks down. Lastly, our sample excludes households who are not planning to purchase a new vehicle, but who may be induced by the PEV rebate policy to purchase a new vehicle. If we had a representative sample of the general population, as opposed to a representative sample of new car buyers, then we could estimate the initial decision to purchase a new vehicle versus a used vehicle or no vehicle. The advantage of focusing on new car buyers is that we obtain a richer data set on decisions to purchase PEVs.

8.3.3 Simulations

We predict PEV sales as follows:

1. For consumer *i* choosing brand k, estimate $Prob_i(M_k)$ for each income class using a rank-ordered logit. Predicted probabilities from this estimation are shown in Table 8-1.

Table 8-1: Estimation Results: Brand Choice

			Probability of Purchase as Estimate by a Rank-Ordered Logit						
	Actual CA Market Share	**Weighted Survey Share**	**All Incomes**	**Income Under $25k**	**Income $25k-$50k**	**Income $50k-$75k**	**Income $75k-$100k**	**Income $100k-$175k**	**Income Over $175k**
Acura	1.40%	3.00%	2.70%	2.70%	2.20%	3.30%	2.30%	2.60%	4.20%
Audi	1.70%	3.80%	3.20%	4.70%	1.10%	2.80%	3.00%	2.80%	9.40%
BMW	4.00%	5.00%	4.50%	3.10%	3.10%	3.60%	4.10%	6.30%	8.40%
Buick	0.50%	1.70%	1.30%	1.90%	0.50%	1.30%	0.30%	2.60%	1.80%
Cadillac	0.80%	1.40%	1.10%	1.50%	0.60%	2.40%	0.70%	0.80%	1.30%
Chevrolet	7.40%	9.00%	8.80%	7.40%	9.70%	8.80%	11.10%	7.60%	4.90%
Chrysler	0.60%	1.60%	1.20%	2.10%	1.70%	0.60%	0.90%	1.40%	0.50%
Dodge	2.20%	2.70%	2.70%	5.70%	3.30%	2.70%	2.30%	1.20%	2.40%
Flat	0.50%	0.70%	1.00%	3.30%	0.40%	0.20%	0.50%	1.30%	0.00%
Ford	10.80%	10.80%	10.90%	10.80%	9.50%	10.00%	12.50%	12.30%	6.50%
GMC	1.40%	1.70%	1.60%	3.00%	3.10%	0.90%	0.70%	1.20%	0.80%
Honda	12.10%	15.20%	15.40%	16.90%	15.50%	17.40%	17.10%	12.20%	12.50%
Hyundai	3.90%	2.90%	3.30%	1.90%	5.00%	3.70%	2.20%	4.10%	1.70%
Infiniti	0.90%	1.20%	1.10%	1.10%	1.00%	0.60%	2.10%	0.90%	0.10%
Jaguar	0.20%	0.10%	0.40%	0.40%	0.10%	0.00%	0.30%	0.90%	0.20%
Jeep	1.90%	1.60%	1.70%	2.20%	2.10%	2.30%	1.10%	1.50%	1.30%
Kia	3.40%	1.70%	2.00%	2.80%	2.50%	1.90%	1.50%	1.90%	0.50%
LandRover	0.50%	0.60%	0.80%	0.10%	1.20%	1.40%	0.80%	0.50%	1.00%
Lexus	3.20%	3.10%	3.40%	1.20%	4.70%	2.90%	2.90%	3.90%	6.20%
Lincoln	0.30%	0.50%	0.80%	1.80%	0.00%	0.20%	0.70%	1.30%	0.80%
Mazda	2.20%	1.50%	1.30%	0.70%	2.30%	0.60%	0.60%	2.00%	1.10%
Mercedes	3.20%	2.20%	2.00%	0.30%	2.00%	1.60%	1.70%	2.70%	4.00%
MINI	0.80%	0.60%	0.50%	0.30%	0.20%	0.70%	0.20%	1.20%	0.30%
Mitsubishi	0.40%	0.20%	0.60%	0.60%	0.80%	1.40%	0.50%	0.00%	0.00%
Nissan	7.50%	4.20%	4.60%	3.90%	5.10%	5.70%	4.80%	4.00%	2.80%
Porsche	0.60%	0.20%	0.40%	0.20%	0.10%	0.60%	0.30%	0.30%	1.50%
Scion	1.00%	0.80%	1.20%	2.80%	0.50%	1.50%	1.80%	0.30%	0.70%
Smart	1.00%								
Subaru	2.50%	2.60%	2.20%	1.40%	3.10%	1.30%	1.30%	2.40%	5.70%
Tesla	0.50%	0.60%							
Toyota	17.50%	15.80%	16.40%	12.50%	16.20%	17.30%	17.90%	16.20%	16.70%
Volkswagen	3.40%	2.00%	2.10%	1.70%	2.10%	1.00%	2.90%	2.70%	1.20%
Volvo	0.40%	0.90%	0.90%	0.90%	0.50%	1.40%	0.70%	0.80%	1.50%

2. For consumer *i* choosing body type k, estimate $Prob_i(B_k)$ using a conditional logit. Covariates include body-specific constants and interactions with number of children and number of cars in household. The estimation results are shown below in Table 8-2. Predicted probabilities of purchasing different body types are different for individuals with different

numbers of children and household vehicles. (Although we tried many other socio-economic variables in these models, we present only those which were statistical significant.) Table 8-3, also below, shows the average probabilities across the sample, estimating the likelihood that a consumer might purchase a vehicle of each body type.

Table 8-2: Estimation Results: Body Choice - Estimated Coefficient

Variable	Estimated Coefficient
Compact Sedan	1.662***
	(0.108)
Midsize Sedan	1.690***
	(0.108)
Full-size Sedan	1.028***
	(0.111)
Compact SUV	1.455***
	(0.110)
Midsize SUV	1.295***
	(0.112)
Full-size SUV	0.667***
	(0.118)
Van or Minivan	-0.497***
	(0.163)
Hatchback	0.616***
	(0.126)
Wagon	-0.394**
	(0.157)
Compact *Number Children	-0.201***
	(0.049)
Midsize *Number Children	-0.171***
	(0.051)
Sportscar *Number Children	0.248***
	(0.030)
Observations	28959

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

Table 8-3: Estimation Results: Body Choice - Average Probability

Body Type	**Average Probability**
Compact Sedan	15.20%
Midsize Sedan	16.00%
Full-size Sedan	9.50%
Compact SUV	12.80%
Midsize SUV	11.10%
Full-size SUV	6.80%
Wagon	2.40%
Hatchback	5.70%
Coupe	7.50%
Van or Minivan	2.20%
Truck	3.50%
Convertible	7.30%

3. Estimate$Prob_i(V_k|M_k, B_k)$ using a conditional logit. Covariates include purchase price (MSRP), refueling cost, electric range, BEV and PHEV constants, and an indicator for single-occupant HOV lane access. Our analysis assumes that the federal tax credit is available to these consumers. The estimation results are shown below in Table 8-4.

Table 8-4: Estimation Results: Vehicle Choice

Variable	Estimated Coefficient
Vehicle Price*Income Under $25k	-0.075***
	(28.000)
Vehicle Price*Income $25-50k	-0.062***
	(23.000)
Vehicle Price*Income $50-75k	-0.048**>K
	(0.016)
Vehicle Price*Income $75-100k	-0.054***
	(0.018)
Vehicle Price*Income $100-175k	-0.038***
	(14.000)
Vehicle Price*Income Over $175k	-0.089***
	(0.025)
BEV*SedanHatchback	-1.989***
	(0.205)
BEV*SUV	-2.090***
	(0.250)
BEV*Sportcar	-2.208***
	(0.278)
BEV*VanTruck	-1.687***
	(0.336)
PHEV	-0.333**
	(0.167)
Range	0.009***
	(0.001)
Refuel	-0.038
	(0.041)
HOV	0.261***
	(0.058)
Observations	24940
Robust standard errors in parentheses	
***p<0.01 ** p<0.05 * p<0.1	

4. Using the representative sample of new car buyers from the survey and the characteristics of existing conventional and PEVs on the market,[49] predict PEV purchase probabilities for each individual in the sample according to Equation 7-14.[50] Integrate PEV purchase probabilities over the weighted sample of new car buyers.

5. Reduce PEV purchase prices by specified rebate amount (assuming the federal tax credit is available) and redo step 4 to predict probabilities of purchasing existing PEVs given the different levels of rebates.

[49] The PEVs on the market as of fall 2013 and their characteristics are shown in Figure 7-A.1 in the Appendix.
[50] We assume that the number of annual new vehicle purchases is constant at 2013 levels for a three year policy period and estimate the number of these purchases that are PEVs. This is reflective of our theoretical and empirical models being contingent upon the decision to purchase a new vehicle.

8.3.4 Comparison of Data and Results to Revealed Preference

In order to validate the new car buyer survey data, we cross-check the respondent characteristics with a sample of new car buyers from the Caltrans 2010-2012 California Household Travel Survey (Caltrans, 2013). These comparisons, shown below in Table 8-5, show that our survey sample is very similar to the actual new car buying population. However, our survey sample has lower household ownership rates and fewer households in the highest income class and with graduate degrees.

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

Table 8-5: UCLA New Car Buyer Survey Population

		Caltrans Survey, Full Population, Weighted Population	Caltrans Survey, New Car Buyers, Weighted Population	UCLA New Car Buyer Survey, Weighted Population
Household Size				
1 person		24.50%	16.30%	13.20%
2 people		30.00%	30.20%	33.50%
3 people		16.40%	18.70%	19.80%
More than or equal to 4 people		29.10%	34.90%	33.40%
Number of Household Vehicles				
None		8.00%	3.70%	2.80%
	1	32.70%	26.30%	29.60%
	2	37.20%	42.90%	42.30%
More than or equal to 3 vehicles		22.00%	27.20%	25.30%
Ethnicity				
White		68.70%	75%	75.30%
African American		4.40%	4%	6.50%
Multi-Racial		7.10%	3%	1.50%
Other		19.80%	18.60%	16.80%
Household Ownership				
Own		72.20%	76.80%	62.00%
Rent		27.60%	23.00%	35.00%
Other		0.10%	0.00%	2.90%
Income				
<10k		5.60%	2.90%	5.10%
10-25k		16.20%	9.80%	7.60%
25k-35k		10.40%	7.40%	7.70%
35k-50k		13.60%	11.70%	9.40%
50k-75k		15.90%	16.10%	16.90%
75k-100k		12.80%	15.20%	22.50%
100k-150k		11.90%	16.10%	18.80%
>150k		13.60%	21.00%	12.10%
Drivers in Household				
None		4.90%	1.60%	0.30%
	1	30.90%	23.20%	19.40%
	2	45.20%	50.90%	51.10%
	3	13.90%	17.40%	16.30%
More than or equal to 4 drivers		5.20%	6.80%	6.80%
Sex				
Male		48.20%	49.10%	51.30%
Female		51.80%	50.70%	48.50%
Age				
Under 18		24.20%	0.10%	0.00%
18-24		10.20%	2.00%	16.20%
25-54		38.50%	50.80%	58.00%

55-64	10.70%	27.70%	14.00%
65 or over	16.50%	19.40%	10.20%
Employment			
Employed	54.00%	66.70%	63.30%
Unemployed	46.00%	32.90%	36.70%
Household Type			
Single family detached	69.20%	74.90%	64.90%
Single family attached	7.80%	7.30%	9.90%
Mobile Home	3.30%	1.90%	2.60%
Building with 2 or more apartments	19.50%	15.70%	22.20%
Boat, RV, Van, etc.	0.00%	0.00%	0.20%
Education			
Not a high school graduate, 12 grade or less	7.40%	3.40%	7.10%
High school graduate	14.80%	11.00%	24.70%
Some college credit but no degree	18.70%	18.10%	23.20%
Associate or technical school degree	11.40%	11.00%	10.60%
Bachelor’s or undergraduate degree	26.20%	30.40%	21.00%
Graduate or professional degree	21.40%	26.00%	13.20%
Vehicle Body Type			
Sedan	47.70%	46.30%	42.20%
SUV	18.00%	19.90%	28.30%
Truck	11.50%	10.50%	3.10%
Coupe	6.50%	6.20%	6.40%
Convertible	1.20%	1.40%	9.80%
Hatchback	3.60%	3.70%	5.60%
Wagon	3.10%	3.30%	2.30%
Minivan or Van	8.30%	8.70%	2.20%

Also shown in Table 8-5 is a comparison of our estimated vehicle class share with the Caltrans 2010-2012 California Household Travel Survey (Caltrans, 2013). Our estimated vehicle class shares are similar to actual market shares as shown in 8-3. The main discrepancies are pickup trucks, minivans, SUVs, and convertibles. As our survey was administered up to three years after the Caltrans survey, the lower estimated share of trucks and minivans may represent the increasing popularity of SUVs for families, for which we estimate a higher share.

We compare our estimated vehicle brand shares with the actual market shares from the California New Car Dealer Association’s California Auto Outlook from the fourth quarter of 2013 (CNCDA, 2013) in Table 8-1. Overall, our estimated brand shares are similar to actual market shares. We also find that higher income households are more likely to select luxury brands.

Our simulations estimate a PEV market share of 3.1% under the rebate policy as it existed during our study period. The actual California PEV market share in the fourth quarter of 2014 was 2.8% (CNCDA, 2015). At the time of the survey, new PEV models were rapidly coming to market. Some of the models available in December of 2013 may not have been available earlier in the fourth quarter. Additionally, consumers may not have had full information about all of the newly available PEVs. This likely accounts for the difference between our estimated market share and the actual market share and also suggests limited hypothetical bias in the choice experiment.[51] In the simulations, if we use the revealed preference brand and body shares from the Caltrans survey and the California New Car Dealer Association, we estimate a PEV market share of 3.0%. If we aggregate body types to two categories, lightweight trucks and cars, we estimate a PEV market share of 3.3%.

In our simulations, we find that the higher income groups purchase PEVs at higher rates (note that the simulation results presented later in the chapter show total PEV sales predicted by income group, but the income groups are of different sizes). We also find by interacting the PEV indicator in the conditional logit model with various demographics that households with more than one vehicle and households that live closer to the coast are more likely to purchase a PEV, although these findings are not statistically significant.[52] These findings are consistent with characteristics of PEV purchasers over the last few years.

Using estimated quantities demanded for each vehicle across each income class before and after the rebate, we estimate an average price elasticity of demand for BEVs of 1.8 and for PHEVs of 2.3. Excluding the top income class, which behaves somewhat differently, we estimate an average income elasticity of demand of 0.2 for BEVs and -0.1 for PHEVs, which reflects the relatively higher rates of BEV purchasers in the top income classes.

The California Clean Vehicle Rebate Project provides rebates of $2,500 for BEVs and $1,500 for PHEVs. As of August 2014 this program had provided more than 50,000 rebates totaling over $100 million since its inception in 2010. Plug-in electric vehicles are also eligible to use high occupancy vehicle lanes in California until January 1, 2019.

8.3.5 Limitations and Extensions: Substitution Possibilities in the Model

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

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

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[51] If respondents believe that their responses will affect policy, strategic behavior would be to understate willingness to pay for PEVs, which would lead to under-estimates of PEV market share.

[52] We find no difference in PEV purchase probabilities between households that live in single, detached houses and those who do not.

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

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

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

8.4 Results and Discussion

We use the simulations we created earlier to evaluate a variety of alternative rebate policy designs. The results are presented in Tables 8-6, 8-7, and 8-9. These results characterize the performance of alternative rebate policy designs over the three-year period from 2014 to 2016 in California.

8.4.1 Simulating the California Rebate Policy

We first simulate the status quo rebate policy in California, which offers all income classes the same rebates of $2,500 for the purchase of a BEV and $1,500 for the purchase of a PHEV. Table 8-6, shown below, includes the baseline number of BEVs and PHEVs purchased by each income class (i.e., the number of BEVs and PHEVs that would have been purchased even if there was no rebate) as well as the additional vehicles induced by the policy design. PHEVs are estimated to represent a higher fraction of purchased vehicles because i) BEVs and PHEVs are assumed to be equally available to consumers and ii) consumers expressed a higher willingness to pay for PHEVs relative to BEVs.

In addition to evaluating the status quo policy, we investigate seven alternate policy designs. Alternative rebate Policies 1 and 2 explore the effects of equalizing the rebates and uniformly lowering the rebates across the vehicle technologies, respectively.

Equalizing rebates across vehicle technologies. Some observers have argued that PHEVs appear to generate similar magnitudes of electric miles traveled; therefore they should be given rebate levels comparable to BEVs. Policy 1 illustrates what might happen in this market if policymakers reduce the BEV rebate by $500 (from $2,500) and increase the PHEV rebate by $500 (from $1,500), making the effective rebate for both vehicle technologies $2,000.

To examine the effects of Policy 1, consider the response of consumers in the $25,000- $50,000 income class in Table 8-6. Compared to the status quo policy, these consumers will purchase slightly fewer additional BEVs (614 versus 775, a decrease of 161 vehicles or 21%) and modestly more PHEVs (1,716 versus 1,278, an increase of 438 or 34%). The large increase in PHEV purchases reflects larger consumer ex ante values for the PHEVs. Therefore, more consumers were relatively more likely to buy PHEVs even before their rebate was increased.

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

This effect also is seen at the programmatic level. In comparing the status quo policy with Policy 1 of equal rebate levels, many more additional vehicles are sold under Policy 1, increasing from 9,699 to 10,602, an increase of 10% in the number of additional PEVs purchased, which is driven by a 30% increase in the number of additional PHEVs purchased. The total cost of the program rises from $291 million to nearly $319 million. This is largely because Policy 1 increases the rebate by $500 to the 99,148 consumers who would have purchased a PHEV in the absence of any rebate, and it induces an additional 7,349 PHEVs to be purchased. This is offset slightly by a $500 rebate reduction to the 49,508 BEVs that would have been purchased without the policy and a reduction in the number of additional BEVs sold by only 848.

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

Uniformly reducing the rebate levels across technologies. Policymakers might consider uniformly reducing rebate levels because of budgetary pressure or a belief that government interventions are no longer justified. In Tables 8-6 and 8-7, Policy 2 reduces both the BEV and PHEV rebate levels by $500, from $2,500 and $1,500, respectively. In comparison with the status quo policy, we observe consumers in all income classes purchasing fewer additional PHEV and BEV vehicles. The total reduction in additional vehicles can be observed by comparing the 6,999 additional vehicles purchased under Policy 2 with the 9,699 additional vehicles purchased under the status quo policy, a difference of roughly 2,700 additional vehicles or a 28% reduction. Total policy costs fall by over $80 million since both the eligible consumers in the baseline and additional consumers all receive lower rebates by $500. However, because of the commensurate fall in the number of additional vehicles under Policy 2, the cost-effectiveness performance of Policy 2, relative to the status quo, improves only a small amount, falling from $30,017 to $29,778.

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

8.4.3 The Effect of a Vehicle Price Cap on Rebate Eligibility

Recently policymakers at the California Air Resources Board have proposed a price cap as means to increase the effectiveness and equity of California's rebate policy. Such a policy design would allow only vehicles below a certain price level to qualify for a rebate. For Policy 3, we consider a vehicle price cap of $60,000, the results of which we present in Tables 8-6, 8-7, and 8-8. For the California market, Policy 3 would historically exclude only the Tesla Model S (a BEV) from a rebate but would prospectively also exclude the Porsche Panamera and the Cadillac ELR (both PHEVs) from a rebate. Our vehicle choice model captures the consumer response for all of these vehicles.

The results of making only vehicles under a price cap of $60,000 eligible for the rebates are shown in Tables 8-6, 8-7, and 8-8 by comparing Policy 3 with the baseline policy. Focusing on where the relative impacts are likely to be greatest, consider consumers with incomes over $175,000 for Policy 3. While these wealthy consumers purchase slightly fewer additional PHEVs (377 vs. 389), they purchase many fewer additional BEVs (194 vs. 557) when shifting from the status quo to a price cap of $60,000. If the policy goal was to give Tesla owners fewer rebates, then this approach appears to succeed. Smaller reductions in relative purchases of PHEVs and BEVs occur for consumers in the other income classes, reflecting the fact that fewer of them are affected by a price cap of $60,000.

In aggregate, the shift from the status quo to a price cap results in a reduction in the total number of additional vehicles being sold (8,651 vs. 9,699, a 10% reduction). This policy design also significantly improves the cost-effectiveness of each additional vehicle sold, causing the cost to fall substantially from $30,017 to $22,075, a 26% reduction. What was perhaps most surprising is how much the total program costs fall, from $291 million to $191 million, a reduction of around $100 million, or 34%.

8.4.4 Income-Tested Rebate Policies

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

Policy 4 assesses an increase in rebate levels but also a cap on income eligibility, meaning consumers above a specified income ($100,000 for this policy) do not qualify for the rebate. All consumers making less than $100,000 would receive a rebate of $5,000 for BEVs and $3,000 for PHEVs. Compared to the status quo policy, this policy design results in significantly more additional PEVs being sold; increasing from 9,699 to 13,471 for a 3,772, or 39% increase. This policy design also represents an increase in cost-effectiveness, dropping from $30,017 to $26,677 for a $3,340 reduction, or an 11% improvement. However, despite reduction in dollars spent per additional vehicle, the 39% increase in the additional number of vehicles sold caused the total cost of this policy design to increase from $291 million for the status quo to $359 million, for an increase of over $68 million, or 23%. Allocative equity increases from 42% for the status quo policy to 73% for this policy. Thus, this policy design improves the number of additional PEVs sold, policy cost-effectiveness, and allocative equity but it does substantially increase the total cost of the program.

We next consider a progressive rebate schedule, which is designed to bring down total program cost. Policy 5 offers progressive rebate levels with an income cap. For BEVs, this policy would offer consumers making 1) less than $25,000, a rebate of $7,500, 2) $25,000- $50,000, a rebate of $5,000, 3) $50,000-$75,000, a rebate of $2,000, and 4) over $75,000, no rebate. Consumers purchasing a PHEV in these same income categories would receive $4,500, $3,000, $1,000, and no rebate respectively. This policy results in approximately the same number of additional PEVs being sold as does the status quo policy: 9,434 vehicles compared to 9,699 vehicles for the status quo. This policy is also among the most cost-effective, at $22,743 per additional PEV purchase induced, compared to $22,075 for the price cap policy (#3). Its total policy costs are also among the lowest of any policy considered so far. This policy has total cost of $215 million compared to $291 million for the status quo policy, a reduction of $76 million or 26%. This policy scores 100% on our allocative equity measure since all of the rebates go to consumers making less than $75,000. The simulation results for Policy 5, therefore, improve on the status quo policy's results along all policy performance dimensions.

8.4.5 Income-Tested Policies with Price Caps

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

Policy 6 evaluates the addition of a vehicle price cap of $60,000 to Policy 4 (Policy 4 generated the largest number of additional PEVs purchased, improved cost-effectiveness, and allocative equity but did so at the largest program costs.). Adding a vehicle price cap as in Policy 6 causes approximately 1,000 fewer vehicles to be purchased compared to Policy 4 but this still represents a 2,753 or a 28% increase in additional vehicles purchased over the status quo policy. Cost-effectiveness improves significantly falling from $26,667 to $21,349 per additional vehicle purchased when comparing Policy 4 and 6. Allocative equity is about the same across policies 4 and 6. However, total program cost falls dramatically from $360 million to $266 million, a $54 million or 15% reduction comparing policies 4 and 6. It should be noted that Policy 6 costs of $266 million are less than the $291 million of the status quo program. Policy 6 also represents an improvement over the status quo policy along all performance dimensions.

Policy 7 adds a vehicle price cap to Policy 5, which has a progressive rebate schedule capping income eligibility at $75,000. Recall that Policy 5 was already superior to the status quo policy along all dimensions. However, adding the vehicle price cap reduces the additional number of vehicles sold to 8,837 from 9,699 under the status quo policy, a reduction of 862 vehicles or 9%. While a net reduction in the number of additional vehicles sold may be viewed as an unacceptable consequence of this policy, it does produce the greatest improvement in policy cost-effectiveness, reducing public dollars spent per additional vehicle from $30,017 to $18,910, a reduction of $11,007 or 37% per vehicle. It also reduces the total program costs from $291 million to $167 million, a savings of $124 million, or 43%.

We should note that these findings assume similar financing and income distribution patterns to those found in the market from 2013 to 2015. In addition, the emergence of a robust used PEV market may decrease demand for new PEVs.

Table 8-6: PEVs Sold by Type of Policy over Three-year Period

Policy	Income	BEV Rebate	PHEV Rebate	Baseline BEVs Sold	Baseline PHEVs Sold	Addt'l BEVs Sold	Addt'l PHEVs Sold	Addt'l PEVs Sold	Total PEVs Sold
Status Quo Policy	Under $25k	$2,500	$1,500	2899	6,203	473	719		
	$25k-$50k	$2,500	$1,500	6065	18,191	775	1,278		
	$50k-$75k	$2,500	$1,500	10313	18,667	664	963	9699	158335
	$75k-$100k	$2,500	$1,500	6349	16,981	645	1,001		
	$100k-$175k	$2,500	$1,500	19322	35,735	985	1,250		
	Over $175k	$2,500	$1,500	4060	3,371	557	389		
Policy 1:									
Equaling Rebates	Under $25k	$2,000	$2,000	2899	6,203	373	305		
	$25k-$50k	$2,000	$2,000	6065	18,191	614	1,716		
	$50k-$75k	$2,000	$2,000	10313	18,667	528	1,290	10602	159258
	$75k-$100k	$2,000	$2,000	6349	16,981	512	1,342		
	$100k-$175k	$2,000	$2,000	19322	35,735	784	1,670		
	Over $175k	$2,000	$2,000	4060	3,371	440	526		
Policy 2:									
Uniformity Decreasing Rebates	Under $25k	$2,000	$1,000	2899	6203	373	512		
	$25k-$50k	$2,000	$1,000	6065	18,191	614	346		
	$50k-$75k	$2,000	$1,000	10313	18,667	528	639	6999	155655
	$75k-$100k	$2,000	$1,000	6349	16,981	512	664		
	$100k-$175k	$2,000	$1,000	19322	35,735	784	332		
	Over $175k	$2,000	$1,000	4060	3,371	440	255		
Policy 3:									
Vehicle Price Cap at $60,000	Under $25k	$2,500	$1,500	2899	6,203	410	719		
	$25k-$50k	$2,500	$1,500	6065	18,191	649	1,269		
	$50k-$75k	$2,500	$1,500	10313	18,667	515	944		
	$75k-$100k	$2,500	$1,500	6349	16,981	507	995		
	$100k-$175k	$2,500	$1,500	19322	35,735	347	1.227		
	Over $175k	$2,500	$1,500	4060	3,371	194	377	8651	157308
Policy 4:									
Aggressive Rebate Increase with Income Cap	Under $25k	$5,000	$3,000	2899	6,203	1,016	1,515		
	$25k-$50k	$5,000	$3,000	6065	18,191	1,629	2,610		
	$50k-$75k	$5,000	$3,000	10313	18,667	1,370	1,954	13471	162128
	$75k-$100k	$5,000	$3,000	6349	16,981	1,342	2,036		
	$100k-$175k	$0	$0	19,322	35,735				
	Over $175k	$0	$0	4060	3,371				
Policy 5:									
Progressive Rebate Increase by Income	Under $25k	$7,500	$4,500	2899	6,203	1,635	2,392		
	$25k-$50k	$5,000	$3,000	6065	18,191	1,629	2,610		
	$50k-$75k	$2,000	$1,000	10313	18,667	528	639	9343	158090
	$75k-$100k	$0	$0	6349	16,981				
	$100k-$175k	$0	$0	19,822	35735				
	Over $175k	$0	$0	4060	3,371				
Policy 6:									
Aggressive Increase with Price Cap	Under $25k	$5,000	$3,000	2899	6203	888	1,515		
	$25k-$50k	$5,000	$3,000	6065	18,191	1,377	2,591		
	$50k-$75k	$5,000	$3,000	10313	18667	1,075	1,915	12452	161108
	$75k-$100k	$5,000	$3,000	6349	16,981	1,069	2,023		
	$100k-$175k	$0	$0	19322	35735				
	Over $175k	$0		4060	3,371				
Policy 7:									
Progressive Rebate with Price Cap	Under $25k	$7,500	$4,500	2899	6203	1,442	2,392		
	$25k-$50k	$5,000	$3,000	6065	18,191	1,377	2,591		
	$50k-$75k	$2,000	$1,000	10313	18,667	408	626	8837	157493
	$75k-$100k	$0	$0	6349	16,981				
	$100k-$175k	$0	$0	19322	35,735				
	Over $175k	$0	$0	4060	3,371				

Micro-dynamics across income groups and vehicle technologies. Next we reflect on two observed patterns predicted earlier by our model that can be observed in the simulation results for the status quo rebate policy as shown in Table 8-6. First, these simulated estimates reflect the consumers' relative ex ante preferences for PHEVs over BEVs in nearly every income class, with consumers in several income classes purchasing 2 to 3 times as many PHEVs as BEVs. Second, in general, the lower income classes have lower ex ante values for both BEVs and PHEVs, purchasing fewer vehicles than do the middle and upper- middle income classes.

We find that lower income classes are typically more responsive to the rebate dollars due to their higher marginal utility of income. Interestingly, consumers in the highest income class (above $175,000) appear to behave somewhat differently (see Table 8-6). Their ex ante value for PEVs is lower than that of the middle income classes, perhaps reflecting their preference for high performance luxury vehicles, which are less likely to be found among existing PEVs. In addition, unlike any other income class, they prefer BEVs (4,060) to PHEVs (3,371), revealing the importance of the Tesla Model S for this income class.

For the status quo policy, the total of additional vehicles purchased across all income classes is estimated to be 9,699 over the three-year period. In Table 8-7, shown below, we calculate the rebate costs by income group and by vehicle technology. Summing the rebates over vehicle type and income class gives us the estimated total status quo program cost of $291 million over the three years.

Table 8-7: PEV Rebate Costs by Type of Policy over Three-year Period

Policy	BEV Income	BEV Rebate	PHEV Rebate	BEV Budget	PHEV Budget	Total PEVs Sold	Total Cost ($ Millions)
Status Quo Policy	Under $25k	$2,500	$1,500	$8,431,349	$10,383,030		
	$25-$50k	$2,500	$1,500	$17,101,072	$29,202,579		
	$50-$75k	$2,500	$1,500	$27,442,629	$29,444,460		
	$75-$100k	$2,500	$1,500	$17,484,884	$26,973,264	158,335	$291
	$100-$175k	$2,500	$1,500	$52,018,618	$55,478,170		
	Over $175k	$2,500	$1,500	$11,541,233	$5,639,740		
Policy 1: Equaling Rebates	Under $25k	$2,000	$2,000	$6,545,083	$14,016,504		
	$25-$50k	$2,000	$2,000	$13,358,461	$39,813,000		
	$50-$75k	$2,000	$2,000	$21,681,786	$39,913,772		
	$75-$100k	$2,000	$2,000	$13,721,774	$36,646,760	159,358	$319
	$100-$175k	$2,000	$2,000	$41,213,544	$74,811,156		
	Over $175k	$2,000	$2,000	$9,000,554	$7,793,533		
Policy 2: Unformly Decreasing Rebates	Under $25k	$2,000	$1,000	$6,545,083	$6,714,527		
	$25-$50k	$2,000	$1,000	$13,358,461	$19,036,334		
	$50-$75k	$2,000	$1,000	$21,681,786	$19,305,549		
	$75-$100k	$2,000	$1,000	$13,721,774	$17,644,670	155,555	$208
	$100-$175k	$2,000	$1,000	$41,213,544	$36,566,955		
	Over $175k	$2,000	$1,000	$9,000,554	$3,626,610		
Policy 3: Vehicle Price Cap at $60,000	Under $25k	$2,500	$1,500	$5,525,708	$8,734,800		
	$25-$50k	$2,500	$1,500	$12,516,008	$26,627,751		
	$50-$75k	$2,500	$1,500	$12,416,557	$20,625,015		
	$75-$100k	$2,500	$1,500	$11,125,314	$23,355,006	157,308	$191
	$100-$175k	$2,500	$1,500	$26,472,618	$40,322,793		
	Over $175k	$2,500	$1,500	$2,510,984	$748,341		
Policy 4: Aggressive Rebate Income with Income Cap	Under $25k	$5,000	$3,000	$19,576,601	$23,152,788		
	$25-$50k	$5,000	$3,000	$38,472,680	$62,401,798		
	$50-$75k	$5,000	$3,000	$58,415,640	$61,862,019		
	$75-$100k	$5,000	$3,000	$38,452,482	$57,049,903	162,128	$359
	$100-$175k	$0	$0	$0	$0		
	Over $175k	$0	$0	$0	$0		
Policy 5: Progressive Rebate Increase by Income	Under $25k	$7,500	$4,500	$34,009,626	$38,679,027		
	$25-$50k	$5,000	$3,000	$38,472,680	$62,401,798		
	$50-$75k	$2,000	$1,000	$21,681,786	$19,305,549		
	$75-$100k	$0	$0	$0	$0	158,090	$215
	$100-$175k	$0	$0	$0	$0		
	Over $175k	$0	$0	$0	$0		
Policy 6: Aggressive Increase with Price Cap	Under $25k	$5,000	$3,000	$13,441,267	$19,856,328		
	$25-$50k	$5,000	$3,000	$28,674,486	$57,222,993		
	$50-$75k	$5,000	$3,000	$27,636,150	$44,163,728		
	$75-$100k	$5,000	$3,000	$25,057,919	$49,793,339	161,108	$266
	$100-$175k	$0	$0	$0	50		
	Over $175k	$0	$0	$0	$0		
Policy 7: Progressive Rebate with Price Cap	Under $25k	$7,500	$4,500	$0	$33,734,336		
	$25-$50k	$5,000	$3,000	$0	$57,222,993		
	$50-$75k	$2,000	$1,000	$0	$13,432,334		
	$75-$100k	$0	$0	$0	$0	157,493	$167
	$100-$175k	$0	$0	$0	$0		
	Over $175k	$0	$0	$0	$0		

Dividing the additional vehicles purchased by the total cost gives us a policy cost-effectiveness measure which we calculate to be $30,017 per additional vehicle as shown below in Table 8-8.

Table 8-8: Comparison of Policy Performance Metrics over Three-year Market Period

Policy	Addt'l PEVs Sold	Addt'l PEVs Sold*	Total Cost-Effectiveness	Addt'l Dollar Needed	Total Cost ($ Millions)	Total Cost* ($ Millions)	Allocative Equity
Status Quo Policy	9,699	N/A	$30,017	N/A	$291	N/A	42%
	10,602	903	$30,044	$27	$319	+$27	42%
		(+9%)		(+0.09%)		(+9.4%)	
	6,999	-2,700	$29,778	-$239	$208	-$83	42%
		(-28%)		(-0.7%)		(-28%)	
	8,651	-1,048	$22,075	-$7,942	$191	-$100	45%
		(-10%)		(-26%)		(-34%)	
	13,471	3,772	$26,677	-$3,340	$359	$68	73%
		(+39%)		(-11%)		(+23%)	
	9,434	-265	$22,743	-$7,274	$215	-$77	100%
		(-3%)		(-24%)		(-26%)	
	12,452	2,753	$21,349	-$8,668	$266	-$25	72%
		(+28%)		(-29%)		(-8.7%)	
	8,837	-862	$18,910	-$11,107	$167	-$124	100%
		(-9%)		(-37%)		(-43%)	
*Compared to Status Quo Policy							

For the status quo policy, every additional PEV purchased (over the baseline of what would have been purchased in the absence of rebates) requires California to spend $30,017 per vehicle. Our simulation suggests that 42% of the value of the rebates allocated goes to households making less than $75,000 under the status quo policy.

The cost effectiveness of the simulated policies is driven by the ratio of marginal to inframarginal PEV purchases, as predicted in Section 8.3. Ultimately, the simulations suggest it is optimal to allocate higher rebates to products for which consumers have lower ex ante values (BEVs) and to consumers who have lower ex ante values (lower-income consumers) because they have fewer infra-marginal purchases. In other words, fewer rebates went to consumers who would have purchased a PEV without a rebate.

The simulations also suggest it is optimal to allocate higher rebates to consumer sectors that may be more responsive to the rebates (in this case, consumers with higher marginal utilities of income are more responsive) because they have more marginal purchases. In Table 8-9, displayed below, we solve for the optimal rebate schedule that maximizes PEV sales, holding the budget equal to the status quo policy.

This policy equalizes the ratio of marginal to non-marginal PEV purchases by allocating higher rebates to consumer segments with lower but steeper demand curves.

Table 8-9: Optimal Policy

Income Level	BEV Rebate	PHEV Rebate	Additional PEVs Sold	Total Cost Effectiveness	Total Cost
Under $25k	$12,500	$7,775	12,995	$22,394	$291,019,864
$25-$50k	$7,400	$2,500			
$50-$75k	$2,500	0			
$75-$100k	$2,500	0			
$100-$175k	0	0			
Over $175k	0	0			

Comparisons with other rebate policies. Our model predicts that 148,636 PEVs would have been sold in the absence of the baseline policy over the first three years of the market. Note, though, that these consumers would still be eligible for the larger federal tax incentive (up to $7,500) as well as local government rebates and reduced-cost parking and charging policies. We find that during our study period, the rebate, which has a weighted value across BEVs and PHEVs of about $1,838, induced the purchase of 9,699 PEVs, a 7% increase in PEV sales, or a 0.2% increase in total market share. As a point of comparison, Sierzchula et al. (2014) use ordinary least squares regression analysis of financial incentives in 30 countries to suggest that an increase in rebate level of $1,000 is correlated with an increase in the observed market share of .06% for PEVs.

We are able to compare this estimate to two other types of vehicle rebate studies, those for hybrid electric vehicles (HEVs) and those for scrappage, or "Cash for Clunkers," programs. Analyzing the Energy Policy Act of 2005, Jenn et al. (2013) find that for most vehicles, rebate levels in the $1,000-$3,000 range are correlated with a 7%-12% increase in sales. Gallagher, Sims, and Muehlegger (2011) find that a tax incentive of $1,000 is associated with a 3%-5% increase in sales for HEVs, while a comparable sales tax waiver is associated with a 45% increase in HEV sales. Analyzing the Canadian Hybrid Electric Vehicle rebate programs in different provinces, a Chandra, Gulati, and Kandlikar (2010) ordinary least squares regression analysis finds that a rebate increase of $1,000 is correlated with an increase in hybrid sales of 26%.

The federal and several state Cash for Clunkers rebate programs have been evaluated. Analyzing the Consumer Assistance to Recycle and Save Act (2009), Huang (2010) uses a regression discontinuity approach to infer that a $1,000 rebate causes a 7% increase in sales of more fuel efficient vehicles. Gayer and Parker (2013) find the same program causes a 6%-15% monthly increase in market share at various months during the program. Other evaluations include Li, Linn, and Spiller (2013) and Mian and Sufi (forthcoming).

Our estimate falls within the range produced by existing studies but is on the lower end of the distribution. That a rebate of a similar magnitude would be slightly less effective for PEVs than for HEVs or other fuel efficient vehicles should not be surprising for several reasons. First, PEVs require consumers to change their refueling practices, including purchasing an at-home charging station in most cases. Second, this study was conducted during a period of high unemployment and relatively lower vehicle purchases than the timeframes used by some of the HEV studies that produced higher market share estimates but did not control for these market conditions (Gallagher, Sims, and Muehlegger, 2011).

8.4.2 Changing Rebate Levels Across Vehicle Technologies

8.6 Conclusion

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

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

Our basic approach enables economists to compare the estimated economic performance of various policy designs. Our specific analysis suggests that policymakers may be able to re-design PEV rebate programs such as California's to induce the sale of more PEVs and achieve greater allocative equity at a lower total cost.

8.7 References

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Chapter 9: Correlation of Gas Price with Plug-in Electric Vehicle Sales

9.1 Introduction

In this chapter we evaluate whether changes in gas prices are correlated with changes in PEV sales. We explore whether consumers respond instantaneously to a change in gas prices or whether there is slight lag in how quickly consumers respond as well as if these effects differ for BEVs and PHEVs. We also examine whether consumers in the very early market (2011-2013) were less responsive to gas price changes in contrast with consumers who purchased vehicles later in the market (2014-15). Finally, we look at regional differences within California.

We cross validate in several ways. First, we will compare our PEVs' results to those of hybrid vehicles as a bench mark. We also explore and compare the effects of different modeling strategies, using both county and census tract level analysis.

Our previous analysis in Chapters 3 and 4 provides important context for this analysis. Most PEV car buyers are wealthier individuals who are relatively less likely to be responsive to changes in gas prices than would more moderate or lower income individuals (Berestanu and Li, 2011) (Klier and Linn, 2010). Therefore increased gas prices would have a larger effect on the sale of used PEVs that lower income individuals are more likely to purchase over new PEVs.

9.2 Descriptive Statistics for Gas Prices

This analysis examines the effect of changing gas prices on plug-in electric vehicle (PEV) purchases in California between January 2011 and January 2016. Table 9-1 shows the mean, median, maximum and minimum monthly gas prices across six major California counties during this time period. Gas prices fluctuated over time, but remained relatively constant across space. In all metropolitan areas, the maximum gas price is nearly two times the minimum price, while the mean gas price in the most expensive metropolitan area (Los Angeles) is less than 25 cents per gallon higher than the mean gas price in the least expensive metropolitan area (Sacramento).

Table 9-1: Gas Prices Between January 2011 and January 2016

County	Mean Price	Median Price	Min. Price	Max. Price
SF-San Jose-Oakland	$3.68	$3.80	$2.37	$4.53
Sacramento County	$3.52	$3.68	$2.17	$4.25
Fresno	$3.58	$3.68	$2.25	$4.30
Los Angeles County	$3.72	$3.80	$2.55	$4.45
Orange County	$3.69	$3.77	$2.54	$4.41
San Diego County	$3.69	$3.78	$2.52	$4.41

Figure 9-1 shows the mean gas price by month for each of the above six metropolitan areas between January 2011 and December 2015. This figure provides a more complete picture of how gas prices have changed over the studied time period. Gas prices were around $4/gallon for much of 2011 and 2012, before dropping to less than $2.50/gallon by the end of 2015. This figure shows again that despite these large swings in prices over time, there is very little cross-sectional difference between the six metropolitan areas in our sample. To the extent that any differences exist, they are limited to differences between Northern/Central and Southern California with almost no difference in price within these larger regions. This lack of regional variation in price is important because it will make it difficult to untangle the unique relationship between gas price and PEV sales.

Figures 9-2 and 9-3 show changes in gas price relative to changes in monthly PEV purchases. Figure 9-2 shows this relationship for all PEVs in Northern/Central and Southern California. We see that at a first glance, monthly PEV sales do appear to stop increasing around the same time gas prices begin decreasing. However, both gas prices and PEV sales exhibit strong seasonal variation, thus it is not clear whether the slowed growth is caused by gas prices, seasonal effects or other factors related to both gas price changes and PEV purchase propensities. Later in our analysis we will control for seasonal variation.

Figure 9-3 shows the relationship between California gas prices and California PHEV and BEV sales. We see that beginning in 2015, PHEV sales fell sharply concurrent with the gas price decline. However, this decline was likely due in part to Toyota's decision to stop production of the Prius PHEV; therefore more advanced statistical analysis is necessary before coming to any stronger conclusions.

Figure 9-1: Average Gas Prices Across Major CA Metro Areas

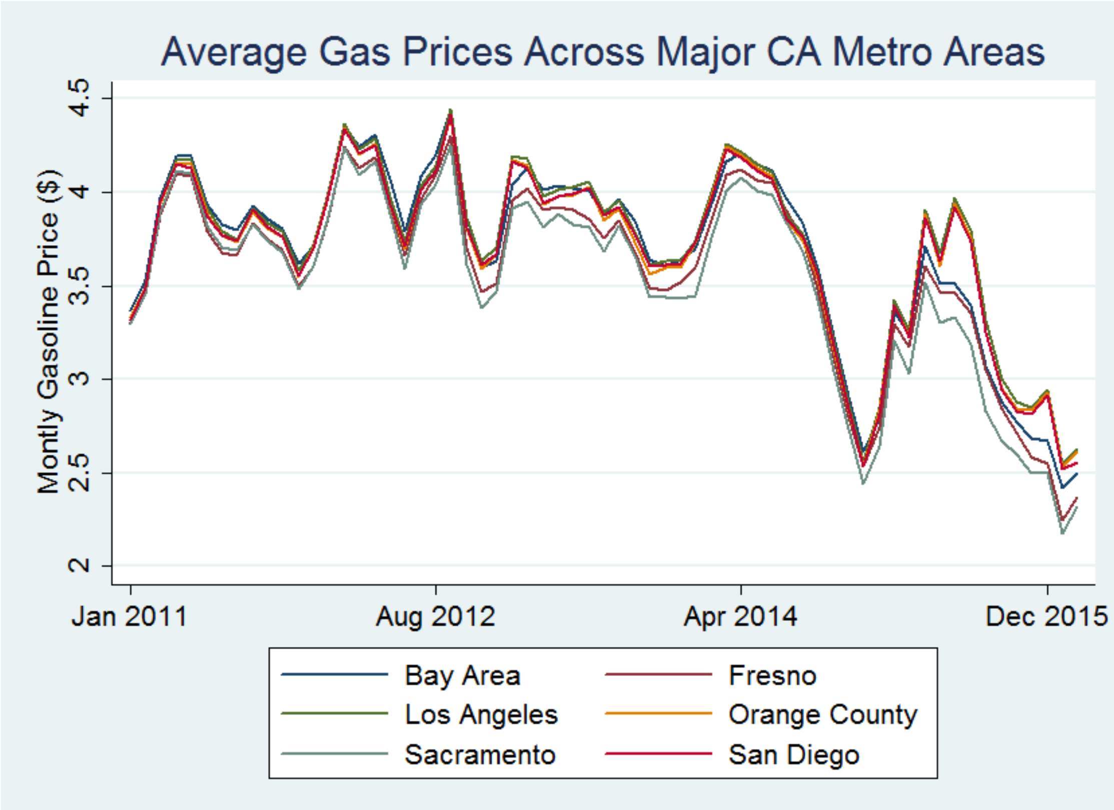


Figure 9-2: Changes in Gas Prices in Relation to PEV Sales

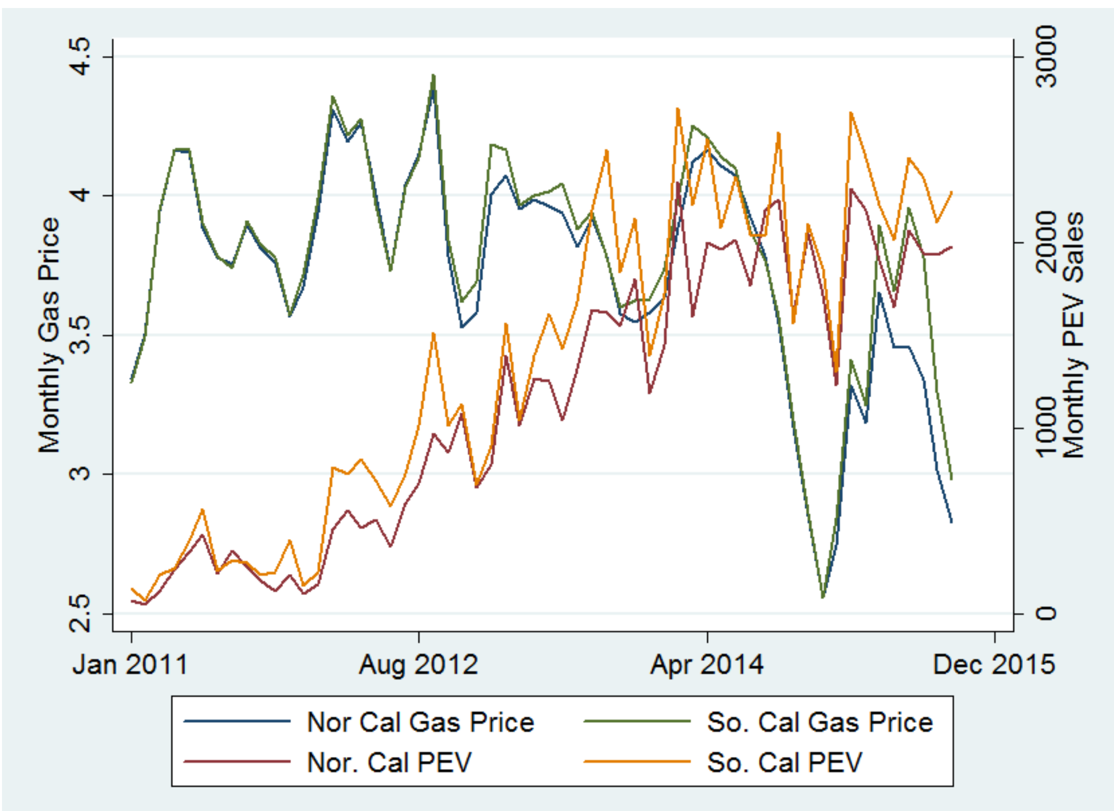
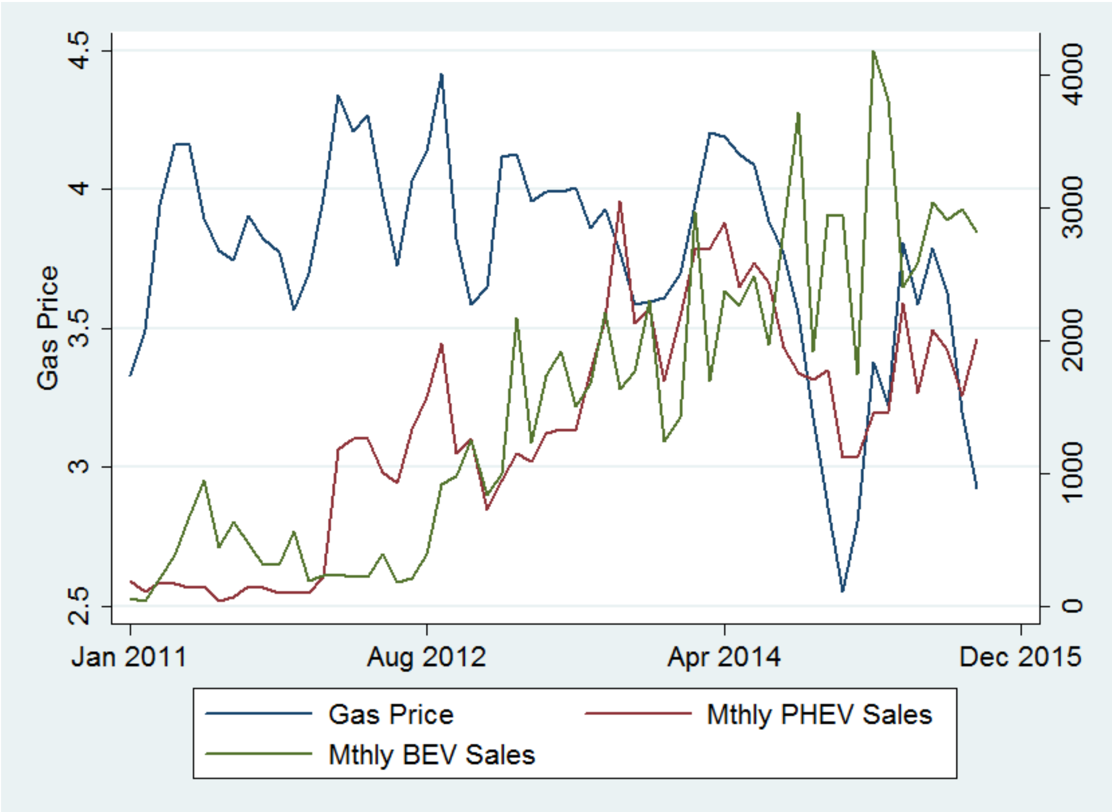


Figure 9-3: Average Gas Price in Relation to BEV and PHEV Sales



Vehicle S

9.3 Gas Prices and PEV Sales at the County Level

We restrict our sample to census tracts in twenty counties for which we have gas price data (listed in Appendix Table 1). These tracts make up more than 90% of all California PEV sales. To analyze the effects of gas price on PEV purchases, we use a series of fixed-effects regressions. Fixed-effect regressions look at the relationships between changes in variables over time and across place, holding constant all place-invariant factors and time-invariant factors. In other words, this model accounts for the factors unique to a specific county that do not change over time that mediate the relationship between gas price changes and PEV sale changes. We aggregate PEV sales up to the county level[53] for the 19 counties on which we have monthly gas price data.

We chose to work at the county level for two reasons. First, our variation in gas price occurs at the county level and so by aggregating PEV sales to the county level we obtain more conservative standard errors. Second, PEV sales are censored at zero from below; that is, although a lower gas price may decrease the propensity to purchase PEVs, if a census tract already has zero sales in a month we will not be able to see this decreased propensity in the data. Since census tracts are relatively small and PEV purchases are relatively less frequent,

[53] We combine Marin County and San Francisco County, Santa Clara and San Mateo County and San Bernardino and Riverside Counties because our gas price data was collected at the metropolitan area, which combines these counties.

many census tracts have a large number of months with zero registrations. There are statistical techniques such as negative binomial regression that can deal with the potential bias caused by this censoring, but they require somewhat strong assumptions. Accordingly, we include such regressions in the appendix to show that our results are generally robust to estimation at the census tract level, while here we restrict our primary analysis to the county-level.

Our fixed-effects regressions will control for any characteristics that affect all counties simultaneously, (e.g. a recession) or one county across our entire time period (e.g. urban areas.) However, we cannot control for county-specific factors that may change over time (i.e. changing local economic conditions). To the extent that these place-specific, time-varying factors are correlated with both the propensity to purchase PEVs and gas prices, they will bias our analyses. Accordingly, all results are better interpreted as associations rather than causal estimates.

Tables 9-2A through 9-2D show the results of our main regressions. Table 9-2A shows the effect of gas prices on total PEV purchases, Table 9-2B on PHEV purchases, Table 9-2C on BEV purchases and Table 9-2D on Hybrid purchases.

Fleet operators may purchase many PEVs which often require lengthy approval processes and negotiations. This creates a disconnect between purchase decision and current gas prices. As a result, all months with more than 13 PEV/month or 36 hybrid/month (.07% of all census tracts) were excluded because it is likely that these vehicles were purchased by commercial or government entities rather than individual consumers.

Columns 1 and 3 include only contemporaneous gas price while columns 2 and 4 include an additional term equal to the average gas price in the three months prior to the baseline period. Columns 1 and 2 include month by year fixed-effects along with controls for county economic variables.[54] This specification holds constant any time-specific factors – other than gasoline prices – that affect all census tracts, but does not control for variables that may be both related to a census tract's propensity to purchase electric vehicles and exposure to higher or lower gas prices (such as urbanization). To better control for these potential omitted variables, we include county fixed effects in Columns 3 and 4. With county fixed-effects we have controlled for all time-invariant county characteristics; accordingly these are our preferred specifications. All standard errors are clustered at the county level in order to correctly interpret the significance level of each variable.

[54] Covariates are: percent of houses worth more than $1,000,000 in the census tract and percent of households earning more than $200,000/year in the census tract

Table 9-2A: Effect of Gas Prices on Total PEV Purchases

VARIABLES	(1) Mthly PEV	(2) Mthly PEV	(3) Mthly PEV	(4) Mthly PEV
Gas Price	820.6***	383.8**	366.2***	132.6
	(80.74)	(157.1)	(71.99)	(99.83)
Avg Gas Price Prv. Qrt.		584.1***		325.1***
		(171.9)		(116.4)
Constant	-2,901***	-3,845***	-1,210***	-1,691***
	(269.6)	(324.1)	(240.4)	(337.6)
Observations	1,098	1,044	1,098	1,044
R-squared	0.300	0.303	0.757	0.782
MonthxYear FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	No	No
County FE	No	No	Yes	Yes

Robust standard errors in parentheses

***p<0.01 ** p<0.05 * p<0.1

Table 9-2B: Effect of Gas Prices on Total PHEV Purchases

VARIABLES	(1) Mthly PHEV	(2) Mthly PHEV	(3) Mthly PHEV	(4) Mthly PHEV
Gas Price	443.0***	194.9*	160.5***	40.21
	(48.89)	(99.78)	(47.30)	(72.88)
Avg. Gas Price Prv Qrt		331.4***		162.7*
		(122.2)		(87.57)
Constant	-1,528***	-2,053***	-525.5***	-743.0***
	(162.3)	(225.1)	(157.9)	(241.6)
Observations	1,098	1,044	1,098	1,044
R-squared	0.262	0.266	0.748	0.772
MonthxYear FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	No	No
County FE	No	No	Yes	Yes

Robust standard errors in parentheses

***p<0.01 ** p<0.05 * p<0.1

Table 9-2C: Effect of Gas Prices on Total BEV Purchases

VARIABLES	(1) Mthly BEV	(2) Mthly BEV	(3) Mthly BEV	(4) Mthly BEV
Gas Price	377.6***	188.9**	205.8***	92.39
	(42.72)	(76.76)	(43.30)	(56.29)
Avg. Gas Price Prv Qrt.		252.7***		162.4***
		(66.44)		(54.20)
Constant	-1,372***	-1,792***	-684.0***	-948.2***
	(145.0)	(149.0)	(144.6)	(167.8)
Observations	1,098	1,044	1,098	1,044
R-squared	0.328	0.329	0.697	0.718
MonthxYear FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	No	No
County FE	No	No	Yes	Yes
Robust standard errors in parentheses				
***p<0.01 ** p<0.05 * p<0.1				

Table 9-2D: Effect of Gas Prices on Total Hybrid Purchases

VARIABLES	(1) Mthly HEV	(2) Mthly HEV	(3) Mthly HEV	(4) Mthly HEV
Gas Price	2,538***	1,211**	654.0***	238.8
	(210.7)	(468.3)	(114.7)	(200.5)
Avg. Gas Price Prv. Qrt.		1,756***		627.0***
		(540.8)		(193.3)
Constant	-8,323***	-11,203***	-1,916***	-2,998***
	(691.2)	(874.8)	(383.1)	(585.0)
Observations	1,098	1,044	1,098	1,044
R-squared	0.168	0.182	0.923	0.926
MonthxYear FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	No	No
County FE	No	No	Yes	Yes
Robust standard errors in parentheses				
***p<0.01 ** p<0.05 * p<0.1				

These results show several interesting patterns. First, we see that our coefficients halve with the addition of county fixed effects; this suggests that there may be important county-specific characteristics related to both gas price and propensity to purchase PEVs. Second, for overall PEV purchases, the current gas price is positively associated with purchase propensity. ***From the average price level, a $1/gallon increase in gas price is associated with 366 greater monthly PEV purchases, holding all else equal.*** This amount is about 225% of the average county monthly PEV purchase. Given the large magnitude of these effects and the caveats mentioned before about potential time-varying omitted variables, these point estimates should be interpreted with caution. However, they do provide suggestive evidence that increased gas prices lead to increase PEV purchases.

Tables 9-2B and 9-2C show the effect broken down separately for PHEVs and BEVs. We see that there is little difference between the two; both PHEV and BEV sales appear to be affected equally by changes in gas prices, with PHEVs being slightly more responsive. Finally, Table 9-2D shows the effect of gas prices on hybrid vehicle sales. We see the effect is similar to that of PEVs. Although the coefficient is a little less than twice as large in absolute terms, it is actually slightly smaller in percentage terms. It is important to note that these coefficients represent the average effect across all counties, but may not describe particularly well the effect in a single county (for instance if a county has a relatively low level of PEV sales, we might not expect a $1/gallon increase in gasoline to lead to such large effects). We attempt to estimate the effect of gas price changes on percent changes in monthly PEV sales in Section 4.

9.4 Validation Analysis: Gas Prices and PEV Sales at Census Tract Level

As mentioned in the introduction, a second possible method of analysis is to analyze purchases at the census tract level using fixed-effect negative binomial regression. This method requires some strong assumptions, but also provides a good robustness check for our primary analysis. Table 9-3 shows our results. The results from the census tract-level fixed-effect negative binomial regression are broadly consistent in direction with our county-level results, but much smaller in magnitude. For instance, in our primary analysis we found that relative to a four month period of $3/gallon gas, a four month period with $4/gallon gas is associated with a 458 vehicle increase in monthly PEV sales for the average county. By contrast, if we perform the same analysis using our results in Table 9-3 (multiplying the effect for a single census tract by 362, the number of tracts in an average county), we find that a $1/gallon increase in the price of gas implies only 11 new vehicles sold, an order of magnitude lower. The effect is larger for BEVs and is actually negative for PHEVs, suggesting that consumers may switch from PHEVs to BEVs in times of high gas prices. Again, given the differences with the county-level analyses, this result should be interpreted with caution. Indeed, these differences highlight the lack of precision available in the present analysis. Although the evidence is consistent with a positive effect of gas prices on PEV sales and suggests a higher effect for BEVs than PHEVs, we cannot estimate the magnitudes of this effect with a high degree of certainty.

Table 9-3: Gas Prices and Vehicle Sales at Census Tract Level

VARIABLES	(1) Mthly PEV	(2) Mthly BEV	(3) Mthly PHEV	(4) Mthly HEV
Gas Price	0.104*	0.180**	0.304***	0.118***
	(0.0568)	(0.0742)	(0.0888)	(0.0442)
Avg Gas Price Prv 3 Mth	-0.0703	0.294***	-0.478***	0.196***
	(0.0779)	(0.0822)	(0.0975)	(0.0514)
Constant	0.722***	-1.115***	0.731***	1.137***
	(0.205)	(0.287)	(0.276)	(0.163)
Observations	377,696	347,072	359,194	396,430
Number of census tracts	6,512	5,984	6,193	6,835

Robust standard errors in parentheses

***p<0.01 ** p<0.05 * p<0.1

9.5 Market Maturity and Regional Differences

Table 9-4 examines consumers' response to gas price changes by year. We might expect that the purchase decisions of early PEV adopters were more motivated by novelty or green preferences and less motivated by fuel savings. Under this hypothesis, PEV consumers in later years may be more likely to resemble more mainstream car buyers and we would expect gas prices to have a significant influence on vehicle choice. Indeed, we find evidence for this hypothesis in our analysis. The gas price coefficients can be interpreted as follows: The undated gas price coefficient is the effect of a $1/gallon price increase on Monthly PEV sales in 2011, the omitted year. The effect of a $1/gallon increase in gas price in all other years is equal to the 2011 gas price coefficient plus the gas price coefficient in Year X. For PEVs, BEVs and PHEVs the effect of gas price increases is much larger in 2014 and 2015 than earlier years. Reassuringly, we see that there is no significant difference across years in the effect of gasoline price on hybrid sales. This is exactly what we would expect from a more mature market.

Table 9-4: Yearly Vehicle Purchases in Relation to Gas Prices

VARIABLES	(1) Mthly PEV	(2) Mthly BEV	(3) Mthly PHEV	(4) Mthly HEV
Gas Price	-99.16	-203.1*	103.9	491.5*
	(201.1)	(113.2)	(104.2)	(260.7)
Gas Price x 2012	-67.75	-78.36	10.62	-144.4
	(187.5)	(106.2)	(96.60)	(226.8)
Gas Price x 2013	280.9	235.7***	45.20	168.2
	(172.9)	(86.64)	(94.64)	(233.9)
Gas Price x 2014	636.5***	362.2***	274.3**	93.83
	(193.0)	(95.95)	(110.9)	(233.9)
Gas Price x 2015	444.7**	392.8***	51.87	198.1
	(189.2)	(105.2)	(97.96)	(253.0)
Constant	344.2	680.9*	-336.7	-1,374
	(674.2)	(377.9)	(350.4)	(876.5)
Observations	1,062	1,062	1,062	1,062
R-squared	0.755	0.698	0.744	0.922
MonthxYear FE	Yes	Yes	Yes	Yes
Covariates	No	No	No	No
County FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

***p<0.01 ** p<0.05 * p<0.1

Finally, Table 9-5 examines whether the effect of gasoline price changes differs by area. We classify our counties into three regions: Northern California (Sacramento, Sonoma, Napa, Marin, San Francisco, Alameda, Contra Costa, Santa Clara, San Mateo, Monterey and Santa Cruz), Southern California (San Luis Obispo, Santa Barbara, Ventura, Los Angeles, San Bernardino, Riverside, Orange and San Diego) and Inland (Fresno, Merced, Yolo).). The coefficients are interpreted the same way as in Table 9-4, above, except this time the coefficient for gas price is the effect on Northern California, the omitted category. We find few significant differences between Northern and Southern California. However, we do find that the positive association between gas prices and PEV purchases is larger in inland California. Inland California is less wealthy and so we might expect fuel savings to have a larger impact on purchase decisions in this region.

Table 9-5: Effect of Gasoline Price Changes by Area

VARIABLES	(1) Mthly PEV	(2) Mthly BEV	(3) Mthly PHEV	(4) Mthly HEV
Gas Price	336.3***	166.1***	170.1***	663.8***
	(89.49)	(59.43)	(38.34)	(156.9)
Gas Price x SoCal	5.921	-15.52	21.44**	20.86
	(21.91)	(16.27)	(9.473)	(26.59)
Gas Price x Inland	74.28***	61.97***	12.31*	11.18
	(14.72)	(10.21)	(6.440)	(13.71)
Constant	-1,158***	-565.8***	-592.4***	-1,982***
	(311.4)	(202.9)	(136.9)	(540.3)
Observations	1,098	1,098	1,098	1,098
R-squared	0.759	0.703	0.749	0.923
MonthxYear FE	Yes	Yes	Yes	Yes
Covariates	No	No	No	No
County FE	Yes	Yes	Yes	Yes

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

9.6 Simulation Exercise

Finally, Table 9-6 shows the predicted effects of a $1 increase in gasoline price for an average county using three different estimates: our primary county-level estimate, our estimate using log monthly purchases and our estimate using the census-tract level approach. This approach shows the large differences between these three models and should highlight the high degree of uncertainty we have about the specific magnitudes of the gasoline effect.

The first four months of Table 9-6 have a gas price of $3 and monthly average sales of 156. Row 3 shows the predicted sales by month after an increase in gas price to $4/gallon, which remains for four consecutive months. We can see that our primary county-level model predicts a huge increase in sales, with sales more than three times as high by month 8 then they were in month 4. By contrast, our model using log monthly sales shows a much more muted response. Sales in month 8 are about 45% higher than they were in month 4. Further, this jump happens almost immediately after the price increase, in this model consumers respond much more to contemporaneous price than they do to historical prices. Finally, in the fifth row, we see the results of the negative binomial fixed-effects model. We extrapolate the coefficient into an average county-level estimate by multiplying the census-tract coefficient by 380, the number of census tracts in the average county in our sample. This effect is even smaller; although the immediate response is very similar to that in the log monthly sales model, this effect diminishes over time. In this model, month 8 sales are only 8% larger than month 4 sales. This wide range of estimates highlights the large level of uncertainty about the effect of gas prices on PEV sales. Although these models provide suggestive evidence that a gas- price hike increases PEV sales, any policy modeling using changes in gasoline prices should examine a wide range of potential effects.

Table 9-6: Simulations of the effects of increasing gas prices on PEV sales

	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Pct Change Month 8 to Month 4
Gas Price	**$3.00**	**$3.00**	**$3.00**	**$3.00**	**$4.00**	**$4.00**	**$4.00**	**$4.00**	
Lagged Qrt Gas Price	**$3.00**	**$3.00**	**$3.00**	**$3.00**	**$3.00**	**$3.33**	**$3.67**	**$4.00**	
Model 1: County Fixed-Effects	156	156	156	156	289	397	505	614	293%
Model 2: County Fixed Effects (Log)	156	156	156	156	206	213	219	226	45%
Model 3: NB Census-Tract	156	156	156	156	196	187	178	169	8%

9.7 Conclusion

Our analysis shows that PEV purchases are positively associated with gas prices. It also provides some suggestive evidence that BEV purchases may be more sensitive to gas prices than PHEVs. However, the magnitude of this association differs by an order of magnitude depending on the model specification and level of aggregation used. Therefore, while this analysis provides strong suggestive evidence that higher gas prices lead to more purchases of PEVs, the extent to which recent gas price decreases have slowed PEV sales remains unclear.

Our analysis also found that PEV consumer sensitivity to gasoline has increased in recent years, consistent with newer PEV buyers focusing on fuel savings rather than novelty or environmental benefits. Additionally, there is evidence of higher gasoline price sensitivity in Inland California, perhaps suggestive of the lower income of consumers in this region.

The results of this analysis should only be interpreted as correlational. There are many possible confounding factors that may be associated with both changing prices and changing PEV purchase behaviors whose effects may be biasing our estimates. Most importantly, varying local economic conditions may be associated with both likelihood of a PEV purchase and relative gas price. Additionally, many models of PEVs are supply-constrained. As a result, suppliers may choose to send more PEVs to areas with higher gas prices further confounding our analysis. Potential solutions to these problems include more granular PEV data (perhaps at the zip code level) or examining differences across states where differences in cross-sectional gas prices over time may be more likely to be caused by distance to refineries and idiosyncratic state policies (gas tax, etc.) rather than local economic conditions. These are all potential areas for future research.

9.8 References

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Klier, T., and J. Linn. (2010), "The Price of Gasoline and New Vehicle Fuel Economy: Evidence from Monthly Sales Data," American Economic Journal: Economic Policy 2: 134–53.

Chapter 10: Conclusion

In this report we first provide an overview of the growth of California's plug-in electric vehicle (PEV) market from 2010 to 2015. We then identify specific neighborhood characteristics and local market factors influencing sales growth. Finally, we evaluate some of the policies that have likely increased PEV market growth.

Broad Market Trends. Our analysis using data provided by HIS Inc. revealed that 125,000 PEVs had been sold in California by the start of 2015. This market share was accomplished via an average annual growth rate of 77% per year from 2010 to 2015, even though PEV sales leveled off in 2015 across the state. By the first quarter of 2014 through the first quarter of 2015, the annual addition by PEVs had reached approximately 3% of total market share in California. The cumulative sale of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) were roughly equal through this period. With respect to vehicle body type, compact cars have lead in annual and cumulative sales over the period of study, but mid-sized and subcompact cars only emerged with significant market share in 2012 and 2013 respectively.

Regional Differences. Significant regional differences exist in terms of cumulative PEVs sold, PEV density and sales rates. The Los Angeles region (Los Angeles and Orange Counties) leads the state in total PEVs purchased, followed by the San Francisco Bay Area Counties and then San Diego County. However, the San Francisco Bay Area Counties have exhibited consistently higher rates of growth, even bucking the slowing statewide trend in 2015. Looking within these major metropolitan areas, PEV purchases are highly spatially concentrated in certain neighborhoods. There are also distinct trends in vehicle type across metropolitan areas. For instance, residents of the San Francisco Bay Area Counties have exhibited a higher propensity to purchase BEVs relative to PHEVs while the Los Angeles Region has exhibited the opposite propensity.

Neighborhood Socio-economic Status and Timing of Market Entry. PEV sales are positively correlated with the socioeconomic status (SES) of neighborhoods as measured by household income, housing values and education. Through October of 2015, neighborhoods ranked in the top 25% by SES status had purchased over 10 times more PEVs than neighborhoods in the bottom 25%, a divergence that appears to be widening over time.

We also considered trends in PEV sales for early- versus late-adopting neighborhoods. Over 24% of neighborhoods had at least one PEV purchaser before July 2011, 50% before July 2012, 72% before July 2013 and 92% before June 2015. Neighborhoods that adopted PEVs earlier exhibited faster purchase growth than neighborhoods that adopted them later. As a result, late adopting neighborhoods do not appear to be catching up with early-adopter neighborhoods.

Predicting PEV Sales Using Neighborhood Characteristics. Our statistical analysis revealed that specific neighborhood characteristics are correlated with PEV sales. Our models were able to explain a substantial proportion, 70-85%, of all observed variation in PEV sales across neighborhoods. The single greatest predictor of PEV sales was a high level of household income within a neighborhood, which explained 60% of the observed differences in PEV sales across neighborhoods. Other positively correlated explanatory factors included household wealth (as represented by housing and rental values), education, race, commuting patterns and access to HOV lanes.

In these same models, when we include variables representing trends in neighborhoods' past PEV purchases, we find early adoption behavior has an independent and positive effect on future sales *even after* accounting for neighborhood differences in the socio-economic variables described above. Importantly, we show that using past trends alone to predict future sales would lead us to under-predict sales in high-income areas and over-predict sales in low-income areas.

Refueling Needs and Fuels. The new car buyer survey also revealed households preferences for longer battery ranges, higher electric fuel efficiency and access to residential and workplace charging. An analysis of changes in gasoline prices revealed that a decrease in gasoline prices (such as occurred in 2015) was correlated with a reduction in plug-in electric vehicles sales.

We also evaluated electricity prices as well as the number of publicly-accessible charging stations within a neighborhood (i.e., census tracts) as potential factors explaining variation in PEV sales. However, we found no statistical correlation with energy prices or neighborhood PEV sales over this period. This lack of association may be due to the fact that both gas and electricity prices remained relatively constant across both time and location from late 2010 to early 2014. However, the lack of a statistically significant correlation between PEV sales and publicly-accessible charging stations within our multivariate analysis cannot be explained in similar fashion.

Predicting BEV Sales Relative to PHEV Sales. We also developed a model to identify characteristics correlated with neighborhoods' propensity to purchase BEVs relative to PHEVs. Our results show that the percent of college graduates was the most important factor associated with relatively higher BEV purchases, followed by commuting patterns, wealth and income. However, this model explained considerably less (only 7%) of the total variation observed across neighborhoods compared to the PEV model discussed above. This may be because the ratio between BEV and PHEVs is naturally highly variable or it may suggest that there may be unobserved factors (such as household preferences) that explain the variation in these ratios.

Predicting Used PEV Sales Across Neighborhoods. We also developed a model which identifies the neighborhood characteristics associated with the purchase of *used* PEVs for the data that became available in 2014 through June of 2015. The model for used PEVs performed very differently from the new PEV model discussed above, suggesting important spatial and socio-economic differences in the determinants of new versus used PEVs. Importantly, the used PEV model suggests that these vehicles will not be as spatially concentrated as new PEVs. While variables representing income, wealth, and education were still among the best predictors of used PEV concentration, the explanatory strength of these factors were not as large as for new PEVs. The used PEV model was not able to predict most of the observed variation (only 17%) in used PEV sales across neighborhoods, suggesting that other variables may influence these sales.

Vehicle Rebate Uptake. The State of California offers Clean Vehicle Purchase Rebates of $1,500 for PHEVs and $2,500 for BEVs to encourage sales. On average 70% of ZEV-buying consumers in California take advantage of these Clean Vehicle Purchase Rebates. Among households that purchase BEVs, about 80% apply for a rebate while about 60% of households purchasing PHEVs apply for this rebate. Over the period of study, considerable variation exists in rebate utilization among vehicle makes purchased as revealed by Nissan at 83%, Tesla and Chevy at 76%, Toyota at 63% and Ford at 57%.

Our statistical model that identifies the correlation of neighborhood characteristics with rebate uptake showed a positive correlation between household income, employment, and percent of Asian residents within a neighborhood and a negative correlation with neighborhoods with lower home values and shorter commutes. However, this model explained only a small amount (5% to 14%) of the observed variation across neighborhoods.

The Effects of HOV-lane Access on PEV Sales. Single-occupancy PEV drivers may access high occupancy vehicle (HOV) lanes in California through 2019. Our analysis suggests that this policy succeeded in increasing PEV sales in neighborhoods with access to HOV lanes. Neighborhoods near HOV lane-miles have a statistically significant increase in PEV sales. We estimated a state-wide causal relationship to show that access to 20, 40, or 140 miles of nearby HOV lanes leads to 2, 4, and 10 additional PEV sales respectively in a census tract. Our simulations show that a 20% reduction/increase in HOV lane-miles would be associated with a 3.8% reduction/2.6% increase in PEV sales in the state of California. These are substantial effects, especially when considering that census tracts are generally only a few square miles in area, meaning that many census tracts can be within a 30-mile radius of an HOV lane-mile.

During our study period, Los Angeles had the highest average number of HOV lane-miles (229) within a 30-mile radius of a census tract, followed by San Francisco (98), Sacramento (38), and San Diego (10). Because adding additional HOV lanes exhibit diminishing returns in PEV sales, our model identifies geographically-specific marginal policy effects that are smaller in Los Angeles, but relatively larger in San Diego, San Francisco, and Sacramento.

Differences in Demand for BEVs and PHEVs. We conducted an analysis of creating BEV and PHEV spinoffs of existing brands and body types for new car buyers in California. To close the gap between a typical consumer's willingness to pay and the current price premium for PEVs, PHEVs require a much smaller rebate than do BEVs. The desired electric vehicle range for the typical PEV purchaser is 165 miles. The typical respondent is willing to pay a purchase price premium of $900 for access to HOV lanes, suggesting (as did our analysis in Chapter 6) that consumers living closer to HOV lanes will be more likely to purchase PEVs than those unable to access them.

Consumer Segmentation for PEVs. Our broader results suggest that there is no "typical" new car buyer. Rather, three very different consumer segments exist in California today with respect to PEVs. One segment representing about a quarter of the new car buyer population seems to be less urban than other segments, more conservative, and have strong negative preferences for all PEVs regardless of whether they are BEVs or PHEVs. A second segment, representing a third of the population has pro-environmental preferences and a tendency for early adoption; this is the only segment that does not have a strong negative preference against BEVs. The third and largest segment tends to be more suburban, slightly older, higher income, and more educated. These consumers exhibit a strong positive preference for PHEVs but also a strong negative preference for BEVs. Their positive preference for PHEVs appears not to stem from environmental or early adopter preferences but rather from the fact that they get better value and have lower operational costs.

The Effects of PEV Rebates on Sales. We assessed the performance of alternative rebate designs for plug-in electric vehicles. The rebate policy in 2014 offered $1,500 and $2,500 rebates for PHEVs and BEVs, respectively, with no income caps. We found that this baseline policy is effective, increasing the PEV market share by at least 7%. We view this as a large and positive effect on the PEV market share.

These analyses were intended to reveal basic facts about the early PEV market. That said, future researchers will want to contrast our characterization of the early PEV market with characterizations of a more mature PEV market.

The Evolution of Policy Research. Future researchers will likely attempt to use new data and new methods to further refine our understanding of the policy effects. Our policy findings that will likely be the subject of continued and future research include:

- The effect of high-occupancy vehicle (HOV) lanes on PEV sales
- The effect of alternative rebate designs on PEV sales
- The effects of new PEV model adoption on aggregate sales
- The most preferred battery range for PEVs

We endeavored to use the latest and best methods available given the data that was available. However, these important policy questions will hopefully be the subject of future research as new data and methods emerge. So these findings will likely be revisited and contested. The future relevance of our findings about consumers will change as consumers themselves change. Their understandings, needs and market choice will evolve continually.

Finally, we also explored several research questions that we could not shed light on because of limits in our available data or methods. These questions focus on:

- The effects of access to public charge stations on PEV sales
- The effects of new PEV model introductions on aggregate PEV sales
- The effects of electricity and fuel prices on PEV sales

We expect that future researchers will be able to provide insights into these questions once they have data on longer periods of market growth.

Glossary

Allocative equity: Fair and impartial apportionment of goods, services or investment. % of rebate revenue allocated to each income class.

Battery electric vehicle (BEV): A type of electric vehicle that is powered by electric motors and motor controllers instead of internal combustion engines.

Binary variable: A variable that can only take two, opposing values (yes or no). For example, do you own a car?

Built-environment: The human created space in which people live, recreate and work. The built environment can encompass material and non-material elements including buildings, parks, neighborhoods, water supplies and energy networks.

Causal relationship: A relationship in which one factor precedes and influences the value of another factor.

Clean vehicles: Vehicles meeting specified emissions standards, generally electric or hybrid vehicles.

Continuous variable: A variable that can have any numerical value between its minimum and maximum value, such as income.

Correlational: A measure of a statistically significant relationship between variables. Variables can be positively or negatively correlated and more or less strongly correlated.

Cost effective: A good value in terms of the goods or services received for money spent. The number of additional PEVs purchased per dollar of public revenue spent.

Crossover utility vehicle (CUV): A vehicle built on a car platform but combining features of a sport utility vehicle (SUV) with features of a passenger vehicle.

Early-adopter: Drivers that purchased electric vehicles soon after they were available on the market.

Electric vehicle (EV): A vehicle that uses one or more electric motors or traction motors for propulsion.

Ex ante: Feelings/hypotheses based on impressions before actually testing something.

Ex post: Feelings/hypotheses based on actual findings after an event or experience.

Externalities: Costs imposed by actors that are not borne by the actors themselves, but instead are imposed on society. For example, the cost of air pollution from motor vehicles.

Fee exemptions: To be free from paying a fee that is typically charged.

Generalized propensity score: A statistical method that attempts to minimize bias when comparing treatment groups to non-treatment groups in observational studies. Generalized propensity score matching allows the researcher to examine continuous variables (e.g. a variable that can have a range of values), not just binary variables.

Heterogeneity: Variability within a statistical distribution.

High occupancy vehicle (HOV): A vehicle containing more than a fixed number of people. HOV lanes are lanes reserved for cars transporting more than a fixed number of riders.

Hybrid electric vehicle (HEV): A vehicle that has both an electric motor and an internal combustion engine.

Hydrogen fuel cell vehicles: Zero-emission vehicles that operate using compressed hydrogen fed into a fuel cell that produces electricity to power the vehicle.

Internal combustion engine (ICE): An engine fueled by gasoline, oil or other fuel.

Knowledge-spillover: Exchange of ideas from an individual or group to another individual or group, often without specific intent. Knowledge-spillover can occur with new technology and can help spread new ideas.

Late-adopter: Drivers that purchased electric vehicles after a longer period of time from when EVs were available on the market than early-adopters.

Latent demand: Also referred to as induced demand, latent demand is when demand increases after the supply of a good increases (more of that good is consumed after supply increases).

Multivariate regression: A statistical estimator where the outcome variable is related to multiple predictors.

Ordinary least squares (OLS): A statistical method of estimating the unknown parameters in a simple linear regression.

Plug-in hybrid electric vehicle (PHEV): A vehicle that has characteristics of both a conventional hybrid electric vehicle and a plug-in electric vehicle.

Policy incentives: Incentives created through public policy meant to encourage a specific behavior or outcome.

Plug-in electric vehicle (PEV): An all-electric vehicle that has a plug to connect to the electrical grid.

Price subsidies: A sum of money given by a public entity or government to support the purchase of a good or service. In this report, price subsidies refer to money used to support the purchase of clean vehicles. Such subsidies can be provided in a variety of ways, but are usually offered to the consumer to help them purchase a clean vehicle that would normally fall outside of their ability to purchase.

Range: The distance which an electric or hybrid electric vehicle can travel on battery power.

Rebates: A partial refund of the cost of a good or service.

Residual: An observable estimate of statistical error in estimation. It is calculated by finding the difference between the observed values and the estimated values of the phenomenon you are investigating.

Retirement and replacement decisions: This report references consumers making retirement and replacement decisions regarding their vehicles. Retirement is the act of getting rid of a vehicle and replacement is the act of getting a new vehicle to replace the old one.

Robustness: The ability of a system or model to tolerate imperfections and problems while still producing reliable results.

Sales tax exemptions: To be free from a sales tax.

Seasonally-adjusted: A statistical method for removing the seasonal component of a time series that exhibits a seasonal pattern.

Socio-economic status (SES): A measure of a person's economic and social position/experience in relation to others, based on income, education, and occupation.

Spatial patterns: Patterns formed by topographical, geometric, or geographic properties.

Standard propensity score matching: A statistical method that attempts to minimize bias when comparing treatment groups to non-treatment groups in observational studies. Standard propensity score matching is only feasible with binary variables (e.g. a variable can only be one or the other of two values).

Subsidized financing: A sum of money given by a public entity or government to support the financing of a good or service.

Tax credits: A tax incentive that allows certain individuals or entities to subtract a defined amount from their taxes. Tax credits have been offered as incentives to customers who purchase clean vehicles.

Temporal patterns: Patterns related to time.

Vehicle miles traveled (VMT): The number of miles traveled by a vehicle in a specific area over a specific period of time.

Willingness to pay (WTP): A person's stated or observed willingness to pay for a good or service. WTP is often used as a proxy for demand of a specific good or service or to define the economic value of a good or service.

Zero-emission vehicle (ZEV): A vehicle that does not emit any tailpipe pollutants, such as particulates, hydrocarbons, carbon monoxide, ozone, lead, or various nitrogen oxides.

Appendix

Chapter 2Appendix: Variables evaluated when analyzing PEV sales

Below is a list of the variables included in our LASSO regressions. There are 225 variables in total. The naming convention is as follows "mainvariable_subgroup". Thus, the variable "male_5under" refers to the number of males in a census tract who are aged 5 and under, while the variable "male" refers to the total number of males in a census tract.

Table A.2-1: All Variables Included in LASSO Regressions

	Variable Names	
ab32yes_percent	age_25to34	pop_familyhousehold_grandchild
Pop	age_35to44	pop_familyhousehold_sibling
Popden	age_45to54	pop_familyhousehold_parent
Area	age_55to64	pop_familyhousehold_parentinlaw
area_land	age_65to74	pop_familyhousehold_siblinginlaw
area_water	age_75to84	pop_familyhousehold_otherrelativ
Male	age_85over	pop_familyhousehold_othernonrela
Female	race_white	pop_nonfamilyhousehold
male_5under	race_black	pop_nonfamilyhousehold_alone
male_5to9	race_native	pop_nonfamilyhousehold_notalone
male_10to14	race_asian	pop_nonfamilyhousehold_nonrelati
male_15to17	race_hawaiian	pop_group
male_18to24	race_other	householdsize_average
male_25to34	race_two	age_25over
male_35to44	Households	education_hsdrop
male_45to54	households_family	education_hs
male_55to64	households_family_married	education_somecollege
male_65to74	households_family_other	education_ba
male_75to84	households_family_male	education_ma
male_85over	households_family_female	education_prof
female_5under	households_nonfamily	education_phd
female_5to9	households_nonfamily_male	age_16over
female_10to14	households_nonfamily_female	employment_laborforce
female_15to17	households_white	employment_military
female_18to24	households_black	employment_civilian
female_25to34	households_native	employment_civilianemployed
female_35to44	households_asian	employment_civilianunemployed
female_45to54	households_hawaiian	employment_nonlaborforce
female_55to64	households_other	employment_total
female_65to74	households_two	industry_ag
female_75to84	households_hispanic	industry_construction
female_85over	households_whiteexhispanic	industry_manufacturing
age_5under	pop_households	industry_wholesale
age_5to9	pop_familyhouseholds	industry_retail

age_10to14	pop_familyhousehold_householder	industry_transportandutilities
age_15to17	pop_familyhousehold_spouse	industry_info
age_18to24	pop_familyhousehold_child	industry_finance
industry_mgmt	mobility_ed_hsless	heat_other
industry_education	mobility_ed_college	heat_none
industry_artsandrec	mobility_ed_grad	housevalue_under20
industry_other	drive_alone_inc10to35	housevalue_20to50
industry_public	drive_alone_inc35to75	housevalue_50to100
income_under10	drive_alone_inc75over	housevalue_100to150
rent_median	income_10to15	housevalue_150to300
mortgages	income_15to20	housevalue_300to500
mortgages_second	income_20to25	housevalue_500to750
mortgages_justone	income_25to30	housevalue_750to1000
povertystatus	income_30to35	Housevalue_over1000
povertystatus_poverty	income_35to40	drive_carpool_inc10to35
povertystatus_above	income_40to45	drive_carpool_inc35to75
commuters	income_45to50	drive_carpool_inc75over
commuters_auto	income_50to60	commute_auto_under15min
commuters_public	income_60to75	commute_auto_15to30min
commuters_motorcycle	income_75to100	commute_auto_30to60min
commuters_bike	income_100to125	commute_auto_over60min
commuters_walk	income_125to150	leavehome_5to6
commuters_other	income_150to200	leavehome_6to7
commuters_home	income_over200	leavehome_7to8
commuters_nothome	households_extraincome	leavehome_8to9
commuters_under10min	households_noextraincome	leavehome_9to10
commuters_10to19min	Houseunits	leavehome_10to12pm
commuters_20to29min	houseunits_owner	leavehome_12pmto4pm
commuters_30to39min	houseunits_renter	leavehome_4pmto12am
commuters_40to59min	houseunits_1unit	Vehicles
commuters_60to89min	houseunits_1detached	Hov_lengthmi
commuters_90minmore	houseunits_1attached	
tenure_same	houseunits_2units	
tenure_county	houseunits_units3to4	
tenure_state	houseunits_units5to9	
tenure_otherstate	houseunits_units10to19	
tenure_abroad	houseunits_units20to49	
native	houseunits_units50more	
foreign_total	houseunits_movile	
foreign_naturalized	houseunits_boatrv	
foreign_notcitizen	houseage_medianyear	
entry_after2010	heat_gas	
entry_00to09	heat_electric	
entry_90to99	heat_oil	
entry_before1990	heat_coal	
mobility_same_30to54	heat_solar	

Chapter 4 Appendix: Full LASSO Regression with (Model 2) and Without (Model 1) County Fixed Effects

Table A.4-1: LASSO Regression Results
(Dependent Variable: Plug-in Electric Vehicles per 1,000)

VARIABLES	(1) pev_per_hh	(2) pev_per_hh
Pop	0.00265	0.00295
	(0.00304)	(0.00286)
ab32yes_pc	-16.60***	-5.609***
	(1.327)	(1.984)
Popden	-0.000187***	-0.000194***
	(1.73e-05)	(1.69e-05)
area_land	-0.00205***	-0.00185***
	(0.000615)	(0.000614)
area_water	0.0791***	0.0879***
	(0.0156)	(0.0153)
male_25to34	0.000449	-7.62e-05
	(0.00105)	(0.00100)
male_35to44	0.00195	0.00261**
	(0.00119)	(0.00113)
male_45to54	0.00283	0.00318*
	(0.00199)	(0.00188)
male_55to64	-0.00108	0.000528
	(0.00154)	(0.00146)
male_65to74	0.00635**	0.00818***
	(0.00317)	(0.00299)
male_85over	-0.000617	-0.00122
	(0.00430)	(0.00406)
female_5to9	0.00529**	0.00440**
	(0.00212)	(0.00199)
female_10to14	0.000194	0.000692
	(0.00161)	(0.00152)
female_15to17	-0.00245	-0.00207
	(0.00201)	(0.00189)
female_25to34	-0.000376	-0.000905
	(0.00120)	(0.00114)
female_35to44	0.000240	0.000497
	(0.00139)	(0.00131)
female_55to64	-0.00292*	-0.00283*
	(0.00162)	(0.00154)
female_85over	-0.00848***	-0.00961***
	(0.00263)	(0.00248)
age_5under	0.00429***	0.00306***
	(0.00110)	(0.00104)
age_5to9	-0.000616	0.000456
	(0.00157)	(0.00148)
age_45to54	-0.00190	-0.00166
	(0.00143)	(0.00135)
age_65to74	-0.00362*	-0.00575***
	(0.00193)	(0.00182)
race_native	0.000741	0.000188
	(0.00145)	(0.00140)
race_black	0.000704	0.00110
	(0.000867)	(0.000819)

race_asian	6.61e-05	-0.000156
	(0.000268)	(0.000259)
race_two	0.00287***	0.00317***
	(0.000810)	(0.000778)
race_other	2.95e-05	-0.000482**
	(0.000234)	(0.000230)
o.race_two	-	-
households_nonfamily_male	-0.00171	-0.00275**
	(0.00138)	(0.00131)
households_black	-0.00459**	-0.00643***
	(0.00220)	(0.00209)
pop_familyhousehold_grandchild	-0.000256	-0.000769
	(0.00130)	(0.00123)
pop_familyhousehold_parentinlaw	0.00881**	0.0107***
	(0.00349)	(0.00329)
pop_nonfamilyhousehold_notalone	-0.00189	0.000173
	(0.00180)	(0.00170)
pop_group	0.000541	-0.000666
	(0.000607)	(0.000582)
householdsize_average	-4.089***	-4.391***
	(0.325)	(0.310)
education_hsdrop	-0.00124	-0.000463
	(0.000846)	(0.000805)
education_somecollege	-0.000401	0.000210
	(0.000816)	(0.000781)
education_ba	0.000309	0.00181**
	(0.000858)	(0.000824)
education_ma	0.00486***	0.00519***
	(0.00125)	(0.00120)
education_prof	-0.00530**	0.00233
	(0.00210)	(0.00204)
education_phd	0.00123	0.000931
	(0.00236)	(0.00225)
employment_military	0.00390***	0.00383***
	(0.00109)	(0.00104)
employment_civilianunemployed	0.00141	0.00133
	(0.00104)	(0.000994)
industry_ag	-0.000217	0.00337***
	(0.00101)	(0.00107)
industry_transportandutilities	-0.00461***	-0.00395**
	(0.00170)	(0.00164)
industry_manufacturing	0.0101***	0.00395***
	(0.00108)	(0.00106)
industry_finance	-0.00735***	-0.00196
	(0.00154)	(0.00148)
industry_education	0.000170	9.11e-05
	(0.000916)	(0.000876)
industry_artsandrec	0.00230**	0.00325***
	(0.00113)	(0.00108)
industry_info	0.00621***	0.00696***
	(0.00192)	(0.00187)
industry_public	-0.00411***	0.00112
	(0.00150)	(0.00151)
income_10to15	0.00234	0.00270
	(0.00209)	(0.00199)
income_20to25	-0.000186	0.00117

	(0.00237)	(0.00224)
income_30to35	-0.00116	0.00167
	(0.00242)	(0.00228)
income_40to45	0.00164	0.00126
	(0.00243)	(0.00229)
income_45to50	-0.00466*	-0.00492**
	(0.00263)	(0.00247)
income_50to60	-0.00304	-0.00330*
	(0.00200)	(0.00189)
income_60to75	-0.00440**	-0.00434**
	(0.00181)	(0.00171)
income_75to100	-0.00485***	-0.00494***
	(0.00169)	(0.00161)
income_125to150	0.000832	0.000337
	(0.00240)	(0.00228)
income_150to200	-0.00306	-0.00168
	(0.00248)	(0.00238)
income_over200	0.0159***	0.0135***
	(0.00244)	(0.00235)
households_extraincome	-0.00395***	-0.00205*
	(0.00125)	(0.00120)
houseunits_1detached	-0.00267***	-0.00237***
	(0.000457)	(0.000453)
houseunits_1attached	-0.00291***	-0.00253***
	(0.000775)	(0.000741)
houseunits_2units	-0.00816***	-0.00829***
	(0.00184)	(0.00177)
houseunits_units3to4	-0.00167	-0.00409***
	(0.00116)	(0.00110)
houseunits_units5to9	-0.00306***	-0.00316***
	(0.00113)	(0.00108)
houseunits_units10to19	-0.00317***	-0.00343***
	(0.00121)	(0.00115)
houseunits_units20to49	-0.00312***	-0.00407***
	(0.00110)	(0.00105)
houseunits_units50more	-0.00215***	-0.00283***
	(0.000688)	(0.000663)
houseunits_boatrv	-0.0177*	-0.0132
	(0.0104)	(0.00986)
houseage_medianyear	-0.000820**	-0.00104***
	(0.000408)	(0.000385)
heat_gas	0.000779	0.000152
	(0.000499)	(0.000531)
heat_other	-0.00454	-0.00543
	(0.00542)	(0.00525)
heat_none	-0.00172	0.00164
	(0.00181)	(0.00178)
heat_solar	-0.0459***	-0.0448***
	(0.0170)	(0.0161)
housevalue_20to50	-0.0118***	-0.0140***
	(0.00331)	(0.00316)
housevalue_100to150	0.00155	-0.000534
	(0.00215)	(0.00205)
housevalue_150to300	-0.000429	-0.000892
	(0.00134)	(0.00128)
housevalue_300to500	-0.000966	-0.00237*
	(0.00134)	(0.00129)

housevalue_500to750	0.00732***	0.00379***
	(0.00146)	(0.00141)
housevalue_750to1000	0.00595***	0.00465***
	(0.00174)	(0.00167)
housevalue_over1000	0.0265***	0.0238***
	(0.00173)	(0.00168)
rent_median	0.00714***	0.00616***
	(0.000374)	(0.000369)
Mortgages	0.000402	0.00228*
	(0.00143)	(0.00136)
mortgages_second	0.00191	0.00360**
	(0.00171)	(0.00162)
commuters_walk	0.00188	0.000811
	(0.00150)	(0.00142)
commuters_home	-0.00155	9.80e-05
	(0.00159)	(0.00152)
commuters_public	-0.00962***	-0.00567***
	(0.00122)	(0.00122)
commuters_under10min	-0.00219**	0.000126
	(0.000898)	(0.000898)
commuters_10to19min	-0.00230***	-0.00114
	(0.000783)	(0.000751)
commuters_40to59min	0.00414***	0.00342***
	(0.00126)	(0.00121)
commuters_60to89min	0.00852***	0.00364*
	(0.00210)	(0.00205)
tenure_same	-0.000184	-0.00203***
	(0.000722)	(0.000711)
tenure_abroad	-0.00579**	-0.00673***
	(0.00245)	(0.00232)
tenure_county	-2.17e-05	-0.00140*
	(0.000768)	(0.000753)
tenure_otherstate	-0.00478***	-0.00593***
	(0.00159)	(0.00152)
Native	-0.00270	-0.00106
	(0.00293)	(0.00276)
foreign_naturalized	0.000947	0.000567
	(0.000778)	(0.000744)
entry_90to99	-0.00101	-0.000767
	(0.00301)	(0.00283)
entry_before1990	-0.00261	-0.000421
	(0.00300)	(0.00282)
Vehicles	0.000422	-9.51e-05
	(0.000379)	(0.000365)
entry_00to09	-0.00184	-0.000428
	(0.00303)	(0.00285)
drive_alone_inc10to35	-0.000893	-0.000939
	(0.000947)	(0.000902)
drive_alone_inc35to75	-0.00106	-0.00265***
	(0.00101)	(0.000969)
drive_alone_inc75over	0.00308**	-0.00107
	(0.00135)	(0.00130)
drive_carpool_inc75over	0.0121***	0.00823***
	(0.00336)	(0.00319)
commute_auto_30to60min	8.99e-05	0.000460
	(0.00104)	(0.000986)
commute_auto_over60min	-0.00845***	-0.00322*

	(0.00177)	(0.00174)
leavehome_5to6	-0.00223*	-0.00290**
	(0.00130)	(0.00125)
leavehome_6to7	-0.00231**	-0.00268***
	(0.00102)	(0.000985)
leavehome_8to9	0.000226	-0.000505
	(0.00104)	(0.000984)
leavehome_9to10	0.00288**	-0.000340
	(0.00138)	(0.00132)
leavehome_10to12pm	0.00495***	0.00218
	(0.00179)	(0.00169)
leavehome_12pmto4pm	-0.000927	-0.000598
	(0.00162)	(0.00154)
leavehome_4pmto12am	-0.00153	-0.00193
	(0.00168)	(0.00159)
Constant	26.04***	31.09***
	(1.450)	(1.460)
County Fixed Effects	N	Y
Observations	7,846	7,846
R-squared	0.714	0.751

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 6 Appendix

Table A.6-1: Descriptive Statistics

	HOV Lanes (30-mile radius)		
Covariate	Bottom Third	Middle Third	Top Third
HOV Lanes within 30-mile Radius	10	116	287
Cumulative PEV Registrations	4	13	8
Cumulative PHEV Registrations	2	7	5
Cumulative BEV Registrations	2	7	3
Population	4,824	4,646	4,466
Commuters	1,974	2,117	2,015
Area (Land, mi2)	48	4	1
Population Density (per mi2)	4,306	8,660	12,660
Prop 23 "Yes" Vote	44%	33%	35%
Avg Gas Price ($)	3.54	3.60	3.63
Avg Electric Price (cents/kWh)	10.5	11.3	10.3
Industry: Construction	4%	4%	3%
Industry: Transport	2%	3%	3%
Industry: Manufacturing	4%	6%	7%
Industry: Agriculture	3%	0%	0%
Industry: Education	11%	13%	12%
Industry: Wholesale	2%	2%	2%
Industry: Management	6%	9%	7%
Employed	53%	59%	58%
Unemployed	8%	7%	7%
Has Mortgage	71%	77%	76%
Has 2nd Mortgage	17%	21%	18%
Income: $10-$15k	6%	4%	6%
Income: $20-$25k	6%	4%	5%
Income: $25-$30k	5%	4%	5%
Income: $35-$40k	5%	4%	5%
Income: $40-$45k	5%	4%	5%
Income: $45-$50k	4%	3%	4%
Income: $50-$60k	8%	7%	8%
Income: $125-$150k	5%	7%	5%
Median Rent ($1,000s)	1.2	1.5	1.3
Median House Value ($10,000s)	29.9	50.0	44.8

	HOV Lanes (30-mile radius)		
Covariate	Bottom Third	Middle Third	Top Third
Commute by Auto: Under 15min	28%	19%	17%
Commute by Auto: 30-60min	21%	26%	30%
Commute by Auto: Over 60min	7%	9%	8%
Leave Home 7-8am	26%	25%	24%
Leave Home 9-10am	6%	9%	9%
Leave Home 10am-noon	5%	5%	5%
Education: High School	23%	19%	21%
Education: Some College	34%	28%	27%
Education: College	49%	51%	45%
Education: MA	6%	10%	6%
Education: Professional Degree	2%	3%	2%
Level 1 Chargers (5-mile Radius)	2	17	8
Level 2 Chargers (5-mile Radius)	21	54	57
DC Chargers (5-mile Radius)	0.2	1.0	0.7

Source: IHS 2010-2015; American Community Survey 2013-2015

Table A.6-2: Number of HOV Miles: p-value of t-test of H0 that populations are the same (reject H0 if p<5%)

Covariate	G1 Adjusted	G1 Unadjusted	G2 Adjusted	G2 Unadjusted	G3 Adjusted	G3 Unadjusted
Population	0.06	0.00	0.17	0.36	0.16	0.00
Population Density	0.00	0.00	0.03	0.01	0.00	0.00
Area (Land)	0.09	0.00	0.11	0.24	0.00	0.00
Commuters	0.08	0.24	0.29	0.00	0.49	0.10
Prop 23 "Yes" Vote	0.00	0.00	0.00	0.00	0.57	0.34
Avg Gas Price	0.01	0.00	0.04	0.53	0.00	0.00
Avg Electric Price	0.00	0.00	0.00	0.00	0.04	0.00
Industry: Construction	0.20	0.12	0.19	0.44	0.32	0.02
Industry: Transport	0.15	0.00	0.57	0.82	0.11	0.00
Industry: Manufacturing	0.03	0.00	0.00	0.00	0.04	0.00
Industry: Agriculture	0.00	0.00	0.02	0.00	0.24	0.00
Industry: Education	0.39	0.90	0.26	0.00	0.11	0.00
Industry: Wholesale	0.03	0.00	0.81	0.00	0.06	0.00
Industry: Management	0.00	0.00	0.01	0.00	0.25	0.00
Employed	0.13	0.00	0.51	0.00	0.17	0.00
Unemployed	0.21	0.00	0.31	0.00	0.31	0.14
Has Mortgage	0.06	0.00	0.03	0.00	0.27	0.76
Has 2nd Mortgage	0.29	0.00	0.44	0.00	0.19	0.00
Income: $10-$15k	0.13	0.04	0.09	0.00	0.20	0.00
Income: $20-$25k	0.16	0.00	0.10	0.00	0.27	0.00
Income: $25-30k	0.18	0.00	0.07	0.00	0.09	0.00
Income: $30-$35k	0.06	0.00	0.10	0.00	0.27	0.00

Covariate	G1 Adjusted	G1 Unadjusted	G2 Adjusted	G2 Unadjusted	G3 Adjusted	G3 Unadjusted
Income: $35-$40k	0.16	0.00	0.10	0.00	0.37	0.00
Income: $45-$50k	0.24	0.00	0.22	0.00	0.20	0.02
Income: $50-$60k	0.13	0.00	0.38	0.00	0.19	0.09
Income: $125-$150k	0.06	0.00	0.31	0.00	0.11	0.00
Median Rent ($1,000s)	0.12	0.00	0.23	0.00	0.24	0.01
Median House Value ($10,000s)	0.00	0.00	0.00	0.00	0.25	0.00
Poverty Rate	0.11	0.00	0.24	0.00	0.09	0.00
Heat: Solar	0.49	0.03	0.40	0.03	0.17	0.00
Heat: Oil	0.24	0.00	0.21	0.22	0.24	0.02
Heat: Electric	0.05	0.00	0.16	0.00	0.05	0.00
Heat: None	0.02	0.00	0.00	0.00	0.18	0.00
Race: Black	0.15	0.00	0.06	0.01	0.24	0.07
Race: White	0.00	0.00	0.00	0.00	0.01	0.00
Race: Asian	0.00	0.00	0.00	0.00	0.30	0.07
Single, Attached House	0.09	0.00	0.17	0.00	0.47	0.40
Single House	0.03	0.00	0.22	0.07	0.00	0.00
Mobile House	0.02	0.00	0.07	0.04	0.19	0.00
Houseunits: 3-4	0.29	0.00	0.59	0.70	0.35	0.00
Houseunits: 10-19	0.26	0.00	0.07	0.00	0.00	0.00
House Value: Under $20k	0.00	0.00	0.40	0.00	0.23	0.00
House Value: $100-$150k	0.00	0.00	0.16	0.00	0.09	0.00
House Value: $150-$300k	0.03	0.00	0.00	0.00	0.25	0.00
House Value: Over $1,000k	0.00	0.00	0.00	0.00	0.09	0.30

Covariate	G1 Adjusted	G1 Unadjusted	G2 Adjusted	G2 Unadjusted	G3 Adjusted	G3 Unadjusted
Male: 25-34	0.23	0.01	0.58	0.10	0.07	0.00
Male: 45-54	0.11	0.00	0.04	0.00	0.53	0.02
Male: 55-64	0.37	0.17	0.10	0.00	0.16	0.00
Male: 75-84	0.04	0.00	0.18	0.09	0.07	0.00
Female: 35-44	0.21	0.00	0.24	0.00	0.20	0.00
Female: Over 85	0.02	0.00	0.82	0.85	0.07	0.00
Age: 15-24	0.15	0.00	0.00	0.00	0.41	0.01
Age: 35-44	0.04	0.00	0.07	0.00	0.08	0.00
Age: 45-54	0.15	0.00	0.03	0.00	0.34	0.00
Age: 65-74	0.10	0.00	0.61	0.66	0.13	0.00
Foreign: Naturalized	0.00	0.00	0.00	0.00	0.09	0.00
Foreign, Entry: 1990-1999	0.32	0.01	0.26	0.00	0.54	0.44
Moved, High School or Less	0.29	0.97	0.08	0.00	0.02	0.00
Moved, College	0.32	0.00	0.18	0.00	0.03	0.00
Moved from Other State	0.21	0.41	0.17	0.33	0.12	0.87
Commute: Walk	0.05	0.00	0.08	0.01	0.48	0.13
Commute: Public Transport	0.00	0.00	0.00	0.00	0.50	0.01
Commute: Motorcycle	0.37	0.01	0.57	0.47	0.88	0.00
Commute by Auto: Under 15min	0.07	0.00	0.00	0.00	0.04	0.00
Commute by Auto: 30-60min	0.02	0.00	0.12	0.14	0.00	0.00
Commute by Auto: Over 60min	0.20	0.00	0.06	0.00	0.45	0.64
Leave Home 7-8am	0.22	0.00	0.33	0.00	0.18	0.00
Leave Home 9-10am	0.00	0.00	0.00	0.00	0.26	0.00

Covariate	G1 Adjusted	G1 Unadjusted	G2 Adjusted	G2 Unadjusted	G3 Adjusted	G3 Unadjusted
Leave Home 10am-noon	0.02	0.00	0.10	0.00	0.38	0.31
Education: High School	0.20	0.00	0.07	0.00	0.19	0.19
Education: Some College	0.00	0.00	0.00	0.00	0.11	0.00
Education: College	0.40	0.00	0.31	0.00	0.02	0.00
Education: MA	0.05	0.00	0.02	0.00	0.15	0.00
Education: Professional Degree	0.11	0.00	0.30	0.00	0.28	0.05
Level 1 Chargers (5-mile Radius)	0.00	0.00	0.00	0.00	0.08	0.00
Level 2 Chargers (5-mile Radius)	0.00	0.00	0.04	0.00	0.05	0.00
DC Chargers (5-mile Radius)	0.00	0.00	0.00	0.00	0.12	0.00

Source: IHS 2010-2015; American Community Survey 2013-2015

Table A.6-3: Stage 1 Estimation Results

	HOV Miles
Population	-6.18e-05*
	(3.49e-06)
Commuters	7.08e-05***
	(7.66e-06)
Population Density	7.12e-06***
	(1.96e-07)
Area (Land)	-0.014***
	0.0003
Prop 23 "Yes" Vote	1.136***
	(0.018)
Avg Gas Price	0.625***
	(0.013)
Avg Electric Price	0.015***
	(0.0006)
Industry: Construction	-1.337***
	(0.065)
Industry: Transport	6.189***
	(0.073)
Industry: Manufacturing	4.406***
	(0.042)
Industry: Agriculture	-20.260***
	(0.185)
Industry: Education	1.883***
	(0.041)
Industry: Wholesale	10.320***
	(0.093)
Industry: Management	-0.631***
	(0.049)
Employed	-0.335***
	(0.040)
Unemployed	0.358***

	HOV Miles
Has Mortgage	-0.247***
	(0.013)
Has 2nd Mortgage	-0.597***
	(0.015)
Income: $10-$15k	-0.872***
	(0.042)
Income: $20-$25k	-0.683***
	(0.046)
Income: $25-$30k	-0.460***
	(0.045)
Income: $30-$35k	-0.200***
	(0.045)
Income: $35-$40k	0.277***
	(0.047)
Income: $45-$50k	0.381***
	(0.049)
Income: $50-$60k	0.399***
	(0.037)
Income: $125-$150k	-0.279***
	(0.039)
Median Rent ($1,000s)	-0.004
	(0.005)
Median House Value ($10,000s)	0.008***
	(0.0002)
Poverty Rate	-0.477***
	(0.024)
Heat: Solar	-8.800***
	(0.379)
Heat: Oil	-8.615***
	(0.328)
Heat: Electric	-0.998***
	(0.013)
Heat: None	2.179***

	HOV Miles
	(0.03)
Race: Black	0.094***
	(0.019)
Race: White	-l.534***
	(0.014)
Race: Asian	-l.931***
	(0.018)
Single, Attached House	-0.018
	(0.013)
Single House	-0.983***
	(0.010)
Mobile House	-0.959***
	(0.021)
Houseunits: 3-4	-0.198***
	(0.020)
Houseunits: 10-19	-0.419***
	(0.022)
House Value: Under $20k	-1.408***
	(0.045)
House Value: $100-$150k	-2.184***
	(0.022)
House Value: $150-$300k	-0.871***
	(0.0001)
House Value: Over $1,000k	-0.424***
	(0.014)
Male: 25-34	0.596***
	(0.055)
Male: 45-54	-1.093***
	(0.106)
Male: 55-64	-0.406***
	(0.071)
Male: 75-84	-0.082
	(0.133)

	HOV Miles
Female: 35-44	-0.142
	(0.100)
Female: Over 85	5.864***
	(0.125)
Age: 15-24	1.042***
	(0.033)
Age: 35-44	1.625***
	(0.064)
Age: 45-54	1.408***
	(0.074)
Age: 65-74	1.831***
	(0.061)
Foreign: Naturalized	1.549***
	(0.026)
Foreign, Entry: 1990-1999	-0.326***
	(0.0134)
Moved, High School or Less	1.058***
	(0.060)
Moved, College	0.814***
	(0.069)
Moved from Other State	-0.388***
	(0.029)
Commute:Walk	0.453***
	(0.037)
Commute: Public Transport	-1.136***
	(0.025)
Commute: Motorcycle	-0.833***
	(0.182)
Commute by Auto: Under 15min	-0.276***
	(0.020)
Commute by Auto: 30-60min	2.517***
	(0.018)
Commute by Auto: Over 60min	2.174***

	HOV Miles
	(0.024)
Leave Home 7-8am	-0.643***
	(0.021)
Leave Home 9-10am	1.282***
	(0.031)
Leave Home 10am-noon	1.203***
	(0.039)
Education: High School	-1.130***
	(0.029)
Education: Some College	-0.676***
	(0.030)
Education: College	-1.217***
	(0.096)
Education: MA	-0.763***
	(0.074)
Education: Professional Degree	0.471***
	(0.095)
Level 1 Chargers (5-mile Radius)	0.004***
	(0.0001)
Level 2 Chargers (5-mile Radius)	-0.001***
	(3.47e-05)
DC Chargers (5-mile Radius)	0.012***
	(0.0008)
Constant	2.940***
	(0.088)
Observations	5,843
Standard errors in parentheses	
***p<0.01 **p<0.05 *p<0.1	

Source: IHS 2010-2015; American Community Survey 2013-2015

Table A.6-4: City Characteristics

	San Diego		Los Angeles		San Francisco		Sacramento	
Variable	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**	**Mean**	**StdDev**
Heat: None	4%	4%	6%	7%	3%	3%	1%	1%
Race: Black	5%	6%	4%	4%	7%	10%	9%	8%
Race: White	73%	16%	56%	19%	52%	21%	63%	19%
Race: Asian	10%	11%	14%	13%	31%	19%	13%	11%
Single, Attached House	9%	10%	6%	6%	18%	17%	7%	7%
Single House	68%	28%	50%	34%	40%	34%	78%	24%
Mobile House	4%	9%	1%	4%	0%	0%	3%	7%
Houseunits: 3-4	5%	6%	5%	7%	12%	11%	7%	9%
Houseunits: 10-19	7%	7%	10%	9%	11%	12%	5%	6%
House Value: Under $20k	2%	6%	0%	2%	0%	2%	2%	5%
House Value: $100-$150k	4%	6%	2%	7%	1%	3%	12%	12%
House Value: $150-$300k	22%	18%	19%	19%	4%	8%	44%	19%
House Value: Over $1,000k	6%	15%	7%	15%	24%	22%	1%	2%
Male: 25-34	8%	4%	9%	4%	11%	6%	7%	3%
Male: 45-54	7%	2%	7%	2%	8%	3%	7%	2%
Male: 55-64	5%	2%	5%	2%	6%	2%	5%	2%
Male: 75-84	2%	1%	2%	1%	2%	1%	2%	1%
Female: 35-44	7%	2%	7%	2%	7%	3%	7%	2%
Female: Over 85	1%	1%	1%	1%	1%	2%	1%	1%
Age:15-24	16%	9%	14%	6%	11%	7%	15%	5%
Age: 35-44	13%	3%	16%	4%	17%	5%	13%	3%
Age: 45-54	14%	4%	14%	3%	14%	4%	14%	3%
Age: 65-74	6%	3%	6%	3%	7%	3%	6%	3%
Foreign: Naturalized	11%	6%	19%	7%	21%	11%	9%	5%
Foreign Entry: 1990-1999	24%	10%	25%	8%	24%	9%	29%	12%
Moved, High School or Less	34%	19%	46%	21%	27%	17%	35%	15%
Moved, College	50%	11%	43%	15%	49%	9%	52%	11%
Moved from Other State	31%	538%	3%	9%	5%	6%	3%	4%
Commut Walke:	3%	4%	3%	4%	10%	11%	2%	4%
Commute: Public Transport	3%	4%	12%	12%	32%	9%	3%	3%
Commute: Motorcycle	0%	1%	0%	1%	1%	1%	0%	1%
Commute by Auto: <15min	21%	8%	15%	7%	8%	4%	21%	8%
Commute by Auto: 30-60min	25%	10%	30%	8%	17%	8%	26%	10%
Commute by Auto: >60min	4%	4%	8%	5%	4%	3%	5%	4%
Leave House 7-8am	25%	6%	25%	7%	26%	7%	27%	7%
Leave Home 9-10am	7%	4%	10%	6%	11%	5%	6%	3%
Leave Home 10am-noon	5%	3%	6%	3%	6%	4%	5%	3%
Education: High School	19%	8%	20%	6%	14%	8%	22%	8%
Education: Some College	32%	9%	24%	7%	20%	6%	36%	7%
Education: College	52%	12%	45%	15%	52%	10%	55%	11%
Education: MA	8%	6%	6%	5%	13%	7%	6%	4%
Education: Professional Degree	3%	3%	2%	3%	5%	4%	2%	3%
Level 1 Chargers (5-mi Radius)	2	3	6	7	71	21	4	7
Level 2 Chargers (5-mi Radius)	58	65	73	53	166	48	47	67
DC Chargers (5-mi Radius)	0.4	0.8	0.5	0.9	0.7	1	0.4	1.2

Source: IHS 2010-2015; American Community Survey 2013-2015

Chapter 7 Appendix

Table A.7-1: Definition of Variables

Variable Name	Description
BEV	Indicator for whether the chosen vehicle is a BEV
PHEV	Indicator for whether the chosen vehicle is a PHEV
Range	Electric range of chosen vehicle (miles)
Refuel	Refueling cost of chosen vehicle ($ per gallon equivalent)
HOV	Indicator for whether the chosen vehicle is granted free single-occupant access to high occupancy vehicle lanes
Small Body	Binary variable for if the respondent indicated that the vehicle she is most likely to select for her next new vehicle purchase is a compact car, midsize car, or hatchback
Household Size	Number of members of household, including respondent
Household Vehicles	Number of vehicles in respondent's household
Age under 35	Binary variable for if respondent is less than 35 years old
Age over 60	Binary variable for if respondent is more than 60 years old
Outlet	Binary variable that equals 1 if the respondent indicated an electrical outlet located within 100 feet of her home parking spot
Single House	Binary variable for if respondent lives in a one-family house detached from any other house or a one-family house or condo attached to one or more houses
Parking at Work	Binary variable for if the respondent indicated she parks her vehicle in a commercial lot or garage while at work
Commute under 20mi	Binary variable for if the respondent indicated that the shortest electric range she would need for daily commute is under 20 miles
Use Gas Mode Daily	Binary variable for if the respondent purchased a PHEV, she anticipates using gasoline mode almost daily
HOV Access	Binary variable that equals 1 if the respondent indicated she could use HOV lanes for her daily commute or weekend travel
Pro Environment	Binary variable for if the respondent indicates that environmental issues are very or extremely important to her personally
Early Adopter	Early adopter score[1]
Liberal	Binary variable for if the respondent identifies her political ideology as liberal (versus conservative or moderate)
Charging Station Density	Publicly available level 2 charging stations within a 5 mile radius of population centroid of the Census Tract in which the respondent (in tens)

Table A.7-1 – continued from previous page

Variable Name	Description
	lives as of December 2013
Gas Price	Average price per gallon of gasoline of the Census Tract in which the respondent lives in December 2013
High Income (>$100k)	Binary variable that equals 1 if the respondent's household income is greater than $100,000
Low Income (<$30k)	Binary variable that equals 1 if the respondent's household income is less than $30,000
College Education	Binary variable for if respondent has a Bachelor's degree or higher education

[1]Early adopter score is between 0 and 5. For each of the five following statements, one point is allocated towards the early adopter score if the respondent agrees or strongly agrees with the statement: (1) I usually try new products before other people do, (2) I often try new brands because I like variety and get bored with the same, (3) When I shop I look for what is new, (4) I like to be the first among my family and friends to try something new, and (5) I like to tell others about new brands or technology

Table A.7-2: UCLA New Car Buyer Survey Population

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

†: Compared to Caltrans (2013) California 2010-2012 Household Travel Survey

Table A.7-3: Estimation Results: Brand Choice

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

Chapter 9 Appendix

Below are the counties included in our analysis. Counties whose gas prices and sales are grouped together are listed on the same line:

- Alameda and Contra Costa Counties
- Fresno County
- Los Angeles County
- Marin County
- Merced County
- Monterey County
- Napa County
- Orange County
- Sacramento County
- San Bernardino and Riverside Counties
- San Diego County
- San Francisco and Marin Counties
- San Luis Obispo County
- San Mateo and Santa Clara Counties
- Santa Barbara County
- Santa Cruz County
- Sonoma County
- Ventura County
- Yolo County