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The Impact of Economic Policies on Heterogeneous Consumers

A dissertation submitted in partial satisfaction
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by

Rongzhang Wang

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ABSTRACT OF THE DISSERTATION

The Impact of Economic
Policies on Heterogeneous
Consumers

by

Rongzhang Wang
Doctor of Philosophy in Economics
University of California, Los Angeles, 2018
Professor Maurizio Mazzocco, Chair

Economic policies can have distributional effects on the market, and often the heterogeneity is tied to the differentiated socio-economic status of consumers. In this dissertation, I study two kinds of policies: rebate programs for clean vehicle buyers, and banking deregulation to stimulate credit supply. The results show that a rationed, income-capped program had large, unexpected spillover effects; while a national policy affected only the lower-valued segment of the housing market.

In Chapter 1, we examine the informational spillover effects on clean vehicles sales associated with a highly-rationed rebate program that targeted moderate to lower lower-income Californians. By exploiting differences of the geographic roll-out in this program, we find that it was associated with approximately at least 2,645 additional clean vehicles sales beyond the 712 vehicles that directly received subsidies. We also calculate the direct environmental benefits of both those vehicles receiving direct subsidies and "spillover" vehicles by estimating local reductions in gasoline consumption and increases in electricity generation attributable to the program, and their marginal effect on human health. Although the per vehicle benefits were lower for the induced "spillover" vehicles then for the subsidized vehicles, the aggregate benefits provided by the spillover vehicles was one third larger than those that were directly subsidized.

Using a structural model, I further explore how subsidies affect electric vehicle sales and

prices, and the welfare consequences of such schemes in Chapter 2. I begin with providing empirical evidence that government incentive programs have helped increase electric vehicle sales. Next, I build and estimate a static market equilibrium model, taking into consideration subsidies, observed and unobserved properties of vehicles, heterogeneous consumer preferences, and marginal cost of production. Finally, I simulate the effects of government incentive programs on electric vehicle sales and prices, and estimate their welfare consequences.

The final chapter is dedicated to the effect of credit market on housing prices. Does a financial market expansion provide the same benefits to households of all income levels? In this paper, we answer the question by studying the 1994 Riegle-Neal Act, a national banking deregulation rule. Our results suggest that the deregulation leads to higher levels of credit supply from banks. And in turn, 1% increase in credit supply leads to 0.51-0.52% increase in the capital gains of lower-valued properties. Median and higher-valued properties are not affected significantly by the credit shock. A possible explanation is that the channels of credit expansion, including lowered down payment, are mostly relevant to low-income home buyers, who are also the major players in the lower-valued property market.

The dissertation of Rongzhang Wang is approved.

George M De Shazo

Edward Chih Yuen Kung

Rosa Liliana Matzkin

Maurizio Mazzocco, Committee Chair

University of California, Los Angeles

2018

To my parents

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CHAPTER 1

Informational Spillover Effects When Clean Vehicle Rebates Are Rationed: Evidence from California's Low-Income Rebate Program

1.1 Introduction

A growing literature has sought to evaluate the direct impacts of clean vehicle rebates on additional vehicle sales (Beresteanu and Li, 2011; Clinton and Steinberg, 2016; DeShazo and Carson, 2017). These rebate programs typically have two components, a financial rebate and an aggressive social marketing of the private and public benefits of clean vehicle adoption to prospective car buyers. To date, studies within the literature have focused exclusively on the impacts of the financial incentives (Clinton and Steinberg, 2016; DeShazo, Sheldon and Carson, 2017) on clean vehicle adoption ignoring any potential informational treatments associated the social marketing component or related informational treatment associated with these programs.

This paper explores whether informational treatment in the context of vehicle rebate programs where rebates are rationed. In many states, policymakers have responded to limited public revenues by limiting or suspending the availability of rebates often for indeterminate periods of time. This policy decision to ration often occurs during periods of relatively heighten consumer awareness of the clean vehicles due to direct marketing campaign, media coverage and social contagion effects. Consumer expectations are often further heighten when policymakers create waiting lists of eligible drivers with the near-term expectation of future funding. Taken together these varied types of informational impacts may "treat" drivers, inducing them to purchase clean vehicles even in the absence of a subsidy.

We evaluate the effects of these informational treatments on vehicle sales when rebates were rationed within California's Enhanced Fleet Modernization and Plus-up Program. This is a vehicle retirement and replacement program targets a range of clean vehicles (hybrids, plug-in hybrids, and battery-only electric vehicles) to low-income households in San Joaquin and South Coast Air Districts within California. The program offers a range of rebates for to households that make less than 225% of the federal poverty limit. It began offering rebates in June 2015 and discontinued by in September 2016, with the creation of a waiting list for customers within the South Coast Air District. Compared with new car rebate programs commonly studied in the literature, this program is unique because it focuses exclusively on moderate to low-income driver and offers, and offers a range of relatively large rebates that can be applied to the purchase of used as well as new clean vehicles.

Our first research objective is to estimate the number and type of clean vehicles that can attributed to the presence of the program but that did not receive rebates from this program. These are clean vehicles sales that resulted the informational treatment of drivers with a robust public education campaigns, media coverage, social network contagion effects and enrollment on rebate waitlists. We exploit the difference of the geographic roll-out in this program, employing a difference-in-difference method to identify the additional increase in vehicle purchases associated with the program. We find surprising large effects from what are essentially information treatments, with at least 2,645 additional clean vehicles sales beyond the 712 vehicles that directly received rebates. This amounts to an increase of 8.8% in clean vehicle sales per 1,000 people. This effect holds across a range of eligible replacement vehicles including both conventional hybrids and plug-in electric hybrids.

Because these informational treatment effects are surprisingly large, we rigorously explore the robustness of these estimates. We show that the treated and untreated zip code areas have the same pre-treatment trend in clean vehicle purchases, satisfying the key assumption of the difference-in-difference method. We also evaluate the size of the treatment effects over different time periods to illustrate the stability of our key findings and implement placebo tests. We explore the potential interaction with a newly modified income-tiered policy in Clean Vehicle Rebate Program, a state-wide subsidy program, starting late March 2016. Finally, we explore the relationship between the treatment effect and the share of low income households in each zip code.

Our second research objective is to estimate the benefits associated with both the vehicles that received a rebate as well as the spillover effects associate with the rationing of clean vehicles rebates. We undertake a welfare analysis using the method taken by Holland et al., (2016), calculating the net benefits of the program by estimating changes in gasoline consumption and electricity generation attributable to the program, and their marginal effect on human health. We estimate that the benefits from vehicles receiving the rebate are $1.9 million while the benefits from the informational spillover vehicles is just over $3.1 million, leading to a total program benefit of $5 million. The welfare effects we find exceed those in Holland et al., (2016), due to the more polluting retired vehicles and the focus on disadvantaged communities in the program we study.

1.2 The EFMP Plus-up Program

Motivated by chronic non-compliance with the US Clean Air Act, California's San Joaquin Valley Air District and South Coast Air Quality Management Districts, began a pilot program on May 27, 2015 the Enhanced Fleet Modernization and Plus-up Program (EFMP & Plus-up) program.[1] These two air districts combined serve a population of nearly 20 million, approximately half of the state's total population.

As shown in Table 1.1 this program provides substantial subsidies to moderate and low-income households who retire an old, polluting vehicle in order to buy a clean replacement vehicle. EFMP Plus-Up utilizes Cap and Trade auction proceeds from the Greenhouse Gas Reduction Fund to augment the original Retire and Replace program (commonly referred to as the "Base" EFMP program) by adding up to an additional $5,000 for a total maximum incentive of $9,500. For example, a low-income participant can receive $9,500 toward the purchase of a plug-in hybrid vehicle with $4,500 coming from the base program and $5,000 from EFMP Plus-Up. Program subsidies are tiered

[1] The EFMP program was originally authorized by Assembly Bill 118 in 2007 (AB 118, "Alternative fuels and vehicle technologies: funding programs," Nunez), with the overarching goal of reducing smog-forming pollutants by targeting the subset of older passenger vehicles that contribute disproportionately to the state's mobile source pollution burden. AB 118 authorized a vehicle registration surcharge to fund EFMP.

Table 1.1: Incentive Scheme of EFMP & Plus-up

Income	Program	8 Years Old or Newer Replacement					
		Conventional 20+ MPG	**Hybrid 20+ MPG**	**Hybrid 35+ MPG**	**PHEV**	**BEV**	**Alternative Transportation**
Low Income≤225% FPL	EFMP	$4,000	$4,000	$4,500	$4,500	$4,500	$4,500
	Plus-up	na	$2,500	$2,500	$5,000	$5,000	
	Total	$4,000	$6,500	$7,000	$9,500	$9,500	$4,500
Moderate Income: 226-300% FPL	EFMP	na	na	$3,500	$3,500	$3,500	$3,500
	Plus-up	na	na	$1,500	$4,000	$4,000	
	Total			$5,000	$7,500	$7,500	$3,500
Above Moderate: 301-400% FPL	EFMP	na	na	na	$2,500	$2,500	$2,500
	Plus-up	na	na	na	$3,000	$3,000	
	Total				$5,500	$5,500	$2,500

Notes: (1) "na" means no subsidies available. (2) Plus-up is only applicable to disadvantaged communities. Source: California Air Resources Board: `https://www.arb.ca.gov/msprog/aqip/efmp/efmp.htm`.

and targeted based on the income of the driver and the type of the replacement vehicle. Eligible drivers' annual income cannot exceed four times the Federal Poverty Line (FPL).[2] In addition, eligible drivers had to retire an older operable high-polluting car and replace it with of a newer clean vehicle. The retirement vehicle had to be at least eight years older than the replacement vehicle, which could include, i) hybrids, ii) plug-in hybrids (PHEVs), and iii) battery electric vehicles (BEVs). The last eligibility requirement is that to receive the Plus-up component, the driver's residential address must be located in zip code as designated as a *disadvantaged community.* These are communities identified as both disproportionate pollution burdens and vulnerabilities as defined by the CalEnviroScreen methodology.

Although marketing of the program differed somewhat across the two air districts, the more heavily populated South Coast Air Quality District employed a multi-faceted, mass media publicity strategy. In addition to the creation of the user-friendly Replace Your Ride website (`http://www.replaceyourride.com`) ,"Replace Your Ride" pamphlets[3]

[2]Federal Poverty Line depends on the number of persons in the household, and adjusts annually. In 2015, for example, the upper bound of income eligibility is approximately $97,000 for a four-person household.

[3]The pamphlets explain to customers that they could receive up to $9,500 towards the purchase of an eligible replacement vehicle. The pamphlets also explain the benefits of advanced technology vehicles

were designed and printed in both English and Spanish, and handed out at "Smog-Less" Saturday events held at routine intervals throughout the district. There was also local television and internet news coverage of the EFMP Plus-Up opportunity for residents of the area. Concerted efforts were made to publicize the program through public events and other forms of community outreach performed by bilingual, contracted case managers.

In total the program processed 773 vehicle acquisitions (purchases or leases) in the first year of operation of the EFMP Plus-Up program, with 361 vehicles placed in the Joaquin Valley Air District and 412 placed in South Coast Air Quality Management District.[4] Rationing occurred almost as soon as the program began. During the first year $3.3 million or 550 vouchers were allocated to the program while more than 1,500 applications were received after media coverage in the early July. The initial funding was exhausted in as early as October 2015. The waiting list of applicants was never empty.

1.3 Estimating Informational treatment effects associated with a Rationed Program

1.3.1 Clean vehicle registration

We use a dataset of clean vehicle registrations in California[5] which contains information for each registered new vehicle, including the make, model, submodel of the car, seller address, buyer address, month of registration. We categorize vehicles into hybrids and plug-in electric vehicles (referred to as PEVs, including PHEVs and BEVs) according to the model, and then count the number of registrations by fuel type, month, and buyer's zip code.[6] We report the results for hybrids and PEVs. The period of study is

including lower-cost of fuel and lower emissions. The pamphlet directs customers to the Replace Your Ride website to fill out a formal application to the program.

[4]Although June 2015 represented the official program start date, the first recorded vehicle transaction occurred on May 25, 2015, as a few pre-pilot transactions were funded by the air districts. Statistics reflected here consequently reflect the period 5/25/2015-5/24/2016.

[5]The clean vehicle registration dataset is provided by Polk.

[6]Out-of-state purchases, trucks and buses, and dealership sales are excluded from the aggregation. They consist of approximately 2% of the entire sample combined.

from January 2014 to September 2016.[7] The period is chosen so that there are enough observations both before and after the program implementation in June 2015.[8]

1.3.2 Disadvantaged zip codes in the two air districts

Table 1.2: Summary Statistics of Disadvantaged Communities by District

	South Coast	San Joaquin Valley	SC & SJV	Other Part of CA
Number of Zipcodes	315	168	483	221
Median HH Income ($)	61,061	48,544	56,707	59,529
Population	39,633	22,185	33,564	28,273
Households	12,062	6,736	10,209	9,335
% Age$\geq$ 25	64.3	59	62.5	65.2
% College+	16.1	8	13.3	15.2
% White	54.1	70.7	59.9	62.8
% Black	8.2	3.5	6.6	7.8
% Other races	19.1	14.4	17.5	10.7

Source: ACS 5-yr 2011-2015.

The EFMP & Plus-up is implemented in San Joaquin Valley and South Coast air districts, consisting of 12 counties in total: Fresno, Kern, Kings, Madera, Merced, San Joaquin, Stanislaus and Tulare in San Joaquin Valley air district, and Los Angeles, Orange, Riverside and San Bernardino in South Coast air district. Table 1.2 reports the demographics in South Coast, San Joaquin Valley, as well as the other parts of California, using the ACS 5-yr 2011-2015 data set.

We study the disadvantaged zip codes in San Joaquin Valley and South Coast, where both the EFMP and the Plus-up components are implemented. We use the CalEnviroScreen (CES) 2.0 scores provided by California Environmental Protection Agency (CalEPA) and its subsidiary agency, the Office of Environmental Health Hazard Assessment (OEHHA), to identify disadvantaged zip codes.

CalEnviroScreen (CES) 2.0 scores, also referred to as the disadvantaged scores in this

[7] Roughly speaking, hybrids entered into the commercial market of California in 2000, while plug-ins entered around 2010.

[8] We assume all vehicles are purchased and registered in the same month. If one bought the car just before the EFMP & Plus-up program, but registered after the program started, this might cause the treatment effect to be over-estimated. We assume that these cases are rare and not significant enough to affect the results.

paper, are directly given to census tracts. OEHHA publishes the scores and deciding factors on their website.[9] The scores depend on pollution levels such as ozone, PM 2.5, pesticides, traffic, etc., as well as demographics such as age, education, poverty, etc. The 25% highest scoring census tracts, together with other high-polluting, low-population areas, are designated as disadvantaged communities.[10] The threshold for the 25% highest scores is a score of 36.62 or above. There are 704 disadvantaged zip codes in California, among which over 70% located in either San Joaquin Valley or South Coast.

To apply for the Plus-up component of EFMP, consumers must have an address within a disadvantaged zip code, defined as a zip code containing all or part of a disadvantaged community.[11] Figure 1.1 presents the California map with disadvantaged zip codes in San Joaquin Valley and South Coast.

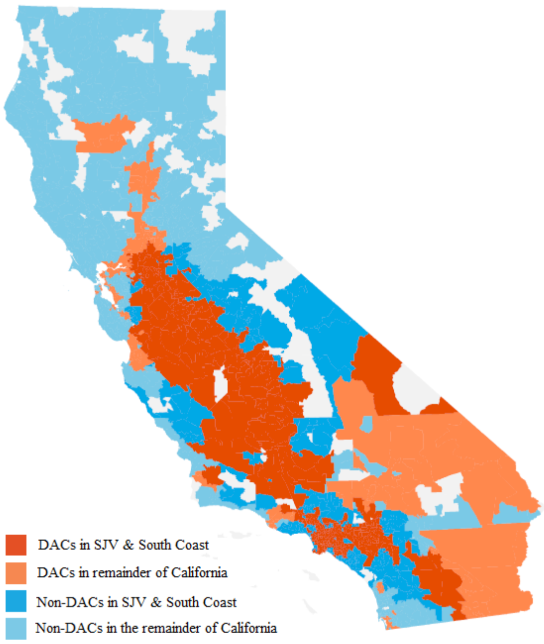

Figure 1.1: Map of California by District and Disadvantaged Status

Figure 1.2 shows the trend of clean vehicle registrations for four geographical groups: disadvantaged communities (DACs) in San Joaquin Valley and South Coast, non-DACs

[9]The latest version at the time of our research is CalEnviroScreen Version 2.0: https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-version-20.

[10]http://calepa.ca.gov/EnvJustice/GHGInvest/.

[11]California Air Resources Board (ARB) provides a list of disadvantaged zip codes: https://www.arb.ca.gov/cc/capandtrade/auctionproceeds/535investments.htm.

in the two regions, DACs in other parts of California, and non-DACs in other parts of California. For each group, we calculate the average clean vehicle registrations per zip code in each month during January 2014 and September 2016. Apart from the total number of clean vehicles, we also report the trends for hybrid, PHEV and BEV registrations, respectively.

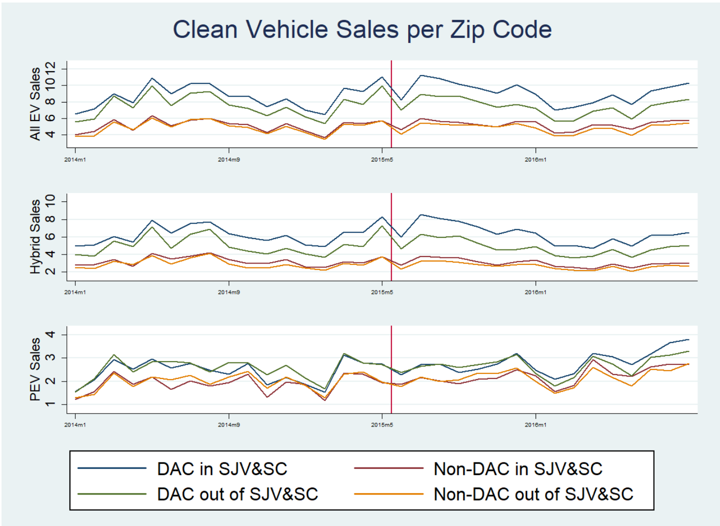

Figure 1.2: The Trend of Clean Vehicle Sales by District and Disadvantaged Status

1.3.3 Program applications

We use the database of successful applications to estimate the direct environmental benefit of the EFMP & Plus-up program. The data covers beneficiaries to either the EFMP only or the EFMP & Plus-up program that locate in San Joaquin Valley and South Coast. For each applicant, the data reports the date of replacement vehicle purchase, household income, retired and replacement vehicle information including make, model, model-year, mileage, etc., as well as rebate amount from EFMP and from Plus-up and loan amount. Table 1.3 shows the distribution of household income, subsidies received, retired car attributes and replacement car attributes in South Coast and San Joaquin Valley, respectively. Successful applicants in San Joaquin Valley, mostly below 225% of FPL in household income, buy cheaper cars while receiving higher subsidies compared to South Coast applicants.

Table 1.3: Statistics of Subsidized Vehicles During the First Year of EFMP Plus-up

	South Coast	San Joaquin Valley
A. Participants by household income category		
Below 225% of FPL	88.4% (364)	99.7% (360)
226-300% of FPL	7.2% (30)	0.3% (1)
301-400% of FPL	4.4% (18)	0% (0)
Total number	412	361
B. Financing characteristics		
Average total incentive	$7,888	$8,120
Total purchase	$21,194	$19,159
C. Retired vehicle attributes		
Average model year	1997	1991
D. Replacement vehicle attributes		
Average model year	2013	2012
New?	120 (29.1%)	0
Hybrid	210 (51.0%)	197 (54.6%)
PHEV	114 (27.7%)	104 (28.8%)
BEV	88 (21.4%)	60 (16.6%)
Total number	412	361

Source: Design and Implementation of the Enhanced Fleet Modernization Plus-up Pilot Programs, UCLA Luskin School of Public Affairs, Luskin Center for Innovation.

1.4 The Impacts on Clean Vehicle Adoption

1.4.1 Empirical strategy

We use the difference-in-difference method to identify the effect of the program. One dimension of difference stems from its timing, while the other dimension is from the geographical restriction.

Geographically, there are three groups in California regarding their status in the program: DACs in San Joaquin Valley and South Coast receive both EFMP and Plus-up; non-DACs in the two districts receive EFMP but not Plus-up; and all zip codes in other parts of California receive neither of the two. To identify the treatment effect of the EFMP & Plus-up, we define the DACs in San Joaquin Valley and South Coast as the treatment group, and the DACs in the other parts of California as the control group accordingly.

Time-wise, we define June 2015 and later to be the post-treatment period, and May 2015 and earlier months to be pre-treatment. Note that the program was announced on May 27, 2015, a few days before June 2015. Considering we only observe the month of vehicle registration, and registrations could be delayed for a few days after purchase, we simply use June 2015 as the start of the program.

The key assumption required is that the treatment and the control group have the same pre-treatment trend in clean vehicle sales. We defend the common trends assumption in two ways. First, Figure 1.3 shows the trends of clean vehicle stocks in the treatment and the control group. The "stock" is defined as the aggregate sales of all advanced technology vehicles, including hybrids, PHEVs and BEVs, from October 2010 to the current month. Hence, monthly sales equal to the slope of the stock. Since monthly sales represent just the slope of the stock, we argue that the two groups have the same pre-treatment trend in sales, and thus the difference-in-difference strategy is valid in identifying the treatment effect.[12] The trend of clean vehicle stock remained almost parallel until June 2015 and separated apart after that. In other words, the two groups had

[12]The advantage of looking at stock rather than sales is that clean vehicle purchases are still relatively rare events, and thus can be affected by large month-to-month random shocks. The trend of sales also supports the argument that they share a similar pre-treatment trend, but with much more fluctuation, as shown in Appendix A1.

Table 1.4: Lead Regression for Pre-treatment Trend Test: Five Pre- and Five Post-Periods

	Y: Clean Vehicle Sales		
	(1)	(2)	(3)
	All Types	Hybrid	PEV
Treated * (Period = -5)	(base)		
Treated * (Period = -4)	0.0975	-0.0825	0.18
	(0.302)	(0.23)	(0.203)
Treated * (Period = -3)	0.359	0.122	0.237
	(0.368)	(0.262)	(0.219)
Treated * (Period = -2)	0.562	0.294	0.268
	(0.355)	(0.263)	(0.201)
Treated * (Period = -1)	0.13	-0.203	0.333
	(0.454)	(0.355)	(0.206)
Treated * (Period = 1)	0.161	-0.0263	0.188
	(0.301)	(0.24)	(0.186)
Treated * (Period = 2)	1.185***	0.929***	0.256
	(0.401)	(0.323)	(0.193)
Treated * (Period = 3)	1.177***	0.957***	0.22
	(0.373)	(0.286)	(0.22)
Treated * (Period = 4)	0.475	0.392	0.0831
	(0.388)	(0.311)	(0.189)
Treated * (Period = 5)	0.695**	0.560**	0.135
	(0.33)	(0.273)	(0.185)
Observations	7,040	7,040	7,040
R-squared	0.03	0.043	0.014

similar pre-treatment trends, but the treatment group had higher post-treatment trend in sales. Alternatively, Table 1.4 presents the similar results using regressions. It tests for whether there was a slope change in the treatment group before the program, using leads of the treatment as explanatory variables. No such trends were found prior to June 2015. Therefore, we argue that the difference-in-difference identification is valid.

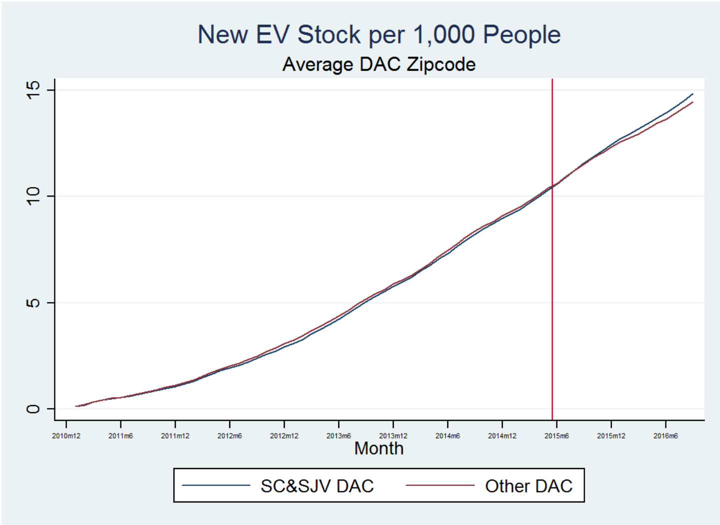

Figure 1.3: The Trend of Clean Vehicle Stock per 1,000 People in Disadvantaged Communities

1.4.2 Regression

The regression we use is the following, using geographical and intertemporal variations to identify the treatment effect:

$$y_{it} = \alpha + \sum_{\tau=1}^{T} \beta_\tau 1\{t = \tau\} + \sum_{\iota=1}^{I} \gamma_\iota 1\{i = \iota\} + \delta D_{it} + \epsilon_{it}$$

We look at the effects on two sets of dependent variables. The first is the clean vehicle sales in zip code i month t, and the second is the sales per 1,000 people in zip code i month t. Both measures have been used in past studies. For example, DeShazo, Sheldon and Carson (2014) and Beresteanu and Li (2011) studied the effect on sales, while Clinton and Steinberg (2017) studied the effect on sales per 1,000 people. Table 1.5 presents the means and standard deviations of the dependent variables in our sample.

We control zip code fixed effects through $\sum_{\iota=1}^{I} \gamma_\iota 1\{i = \iota\}$. The purpose is to separate time-invariant characteristics from our treatment effect. Many factors, including population, income, education, environmental-related attitudes, HOV lane length etc., are time-invariant during the relatively short period from 2014 to 2016.

Table 1.5: Summary Statistics for Dependent Variables Pre/Post-Treatment

	Treatment Group		Control Group	
	Before	After	Before	After
Sales				
Hybrids	6.27	6.35	5.08	4.76
	(6.37)	(6.36)	(5.36)	(4.87)
PEVs	2.42	2.82	2.55	2.68
	(3.22)	(3.75)	(4.38)	(4.72)
Total	8.69	9.16	7.62	7.44
	(8.93)	(9.32)	(8.77)	(8.55)
Sales per 1,000 People				
Hybrids	0.19	0.19	0.18	0.16
	(0.18)	(0.18)	(0.16)	(0.15)
PEVs	0.08	0.09	0.09	0.09
	(0.10)	(0.13)	(0.13)	(0.15)
Total	0.27	0.28	0.27	0.25
	(0.26)	(0.28)	(0.25)	(0.25)

Source: Vehicle registration from IHS Markit.

Time fixed effects are controlled using $\sum_{\tau=1}^{T} \beta_\tau 1\{t = \tau\}$. As a result, common trends that may affect clean vehicle sales in all zip codes are excluded from our estimates, to name but a few, seasonal effects, gas price fluctuations, electricity price changes, growth of charging station networks common to all zip codes, etc.

The rest of the variation is either associated with the EFMP & Plus-up, which is captured by δ as the treatment effect or considered as random shock ϵ_{it}. D_{it} equals 1 if zip code i belongs to the treatment group and is treated in month t, and equals 0 otherwise.

The identification strategy will be threatened if there are time-varying, geographically heterogeneous factors that affect the outcome variable during the period of study. One potential threat to our identification is the change of the CVRP program mentioned previously that started on March 29, 2016. In short, CVRP used to offer flat-rate rebate

Table 1.6: The Percentage of Households Income Smaller or Equal to 3 Times FPL

	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**
Control Group	218	0.56	0.18	0	0.97
Treatment Group	481	0.61	0.18	0.16	0.95

Source: ACS 5-yr 2011-2015.

to PEV buyers in California but began to favor low income applicants afterwards. It would lead to over-estimation of the treatment effect if low income households are disproportionally concentrated in the treatment group than the control group. Table 1.6 compares the percentage of households with income smaller than or equal to 300% FPL, i.e. the low-income threshold adopted by the CVRP subsidy, in the treatment and the control group. We will also discuss more about the possible interaction between the two programs in the next section.

1.4.3 Main results

Panel A of Table 1.7 presents the main results for difference-in-difference regressions. The outcome of interest is clean vehicle sales in Column (1) to (3), and sales per 1,000 people in Column (4) to (6). Treatment effects in the six specifications are all significantly positive. The EFMP & Plus-up leads to an additional 0.659 clean vehicles sold monthly per zip code during June 2015 and September 2016, or 0.0268 vehicles per 1,000 people. Considering that the average monthly sales of clean vehicles pre-treatment are approximately 8.69 per zip code, it represents an increase of 7.6%. Moreover, the effect holds across different types of vehicle technology, with hybrid sales increased more (0.391 vs. 0.268 vehicles, or 0.0152 vs. 0.0115 vehicles per 1,000 people monthly per zip code), which is not surprising considering the scale of hybrid sales had been larger than that of PEVs. Per capita-wise, the results indicate an 10% increase associated with the treatment, with the monthly sales of clean vehicles per 1,000 people being 0.267 on average pre-treatment.[13]

[13] As a cross reference, In the United States, Beresteanu and Li (2011) studied the effect of the federal tax incentives on Hybrids in 2006, and estimated an increase of 19.75% with $2,276 per car on average. DeShazo, Sheldon and Carson (2014) surveyed potential Plug-in and Battery-only EV buyers in California, and simulated that there will be 9,699 more EVs sold, an increase of 6.67%, with $2,500 subsidy for Battery-only and $1,500 for Plug-in. In Japan, Alhulail and Takeuchi (2014) studied the effect of two tax incentive programs which raised Eco-Car sales by 21.5% and 10.7%, respectively.

Table 1.7: Treatment Effects of EFMP Plus-up on Clean Vehicle Adoptions

	Y: Clean Vehicle Sales			Y: Density of Clean Vehicle Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Types	Hybrid	PEV	All Types	Hybrid	PEV
Panel A. Baseline Regression						
Treated*After	0.659***	0.391***	0.268***	0.0268***	0.0152***	0.0115***
	(0.0874)	(0.0712)	(0.0492)	(0.00361)	(0.0029)	(0.00209)
R-squared	0.155	0.15	0.074	0.097	0.096	0.044
Observations	23,232	23,232	23,232	23,232	23,232	23,232
Number of zip	704	704	704	704	704	704
Panel B. Robust Check: Synthetic Control						
Treated*After				0.0231***		
				(0.00173)		
R-squared				0.139		
Observations				20,244		
Number of zip				483		
Panel C. Robust Check: Placebo Test						
Treated*After	0.172*	0.322***	-0.150***	0.00597	0.00903***	-0.00306
	(0.094)	(0.0774)	(0.05)	(0.00386)	(0.00321)	(0.00205)
R-squared	0.177	0.137	0.138	0.106	0.083	0.087
Observations	20,416	20,416	20,416	20,416	20,416	20,416
Number of zip	704	704	704	704	704	704

In sum, our estimate is 10% increase in clean vehicle sales per 1,000 people in the most preferred setting, in response to around $7,292 per car on average. Note that this is the effect on the new clean vehicles market, where most consumers exceed the income cap to apply for the EFMP & Plus-up subsidy.

Table 1.8 replicates the baseline regression in South Coast and San Joaquin Valley, respectively, to reveal the heterogeneity between the two markets. Although the impacts in San Joaquin Valley are still found to be significant, they are much smaller in scale compared to South Coast. While contributing to an additional clean vehicle sale of 0.907 per zip code in South Coast, the program increased the sales in San Joaquin Valley by

Table 1.8: Treatment Effects of EFMP and Plus-up By Region: January 2014 to September 2016

	Y: Clean Vehicle Sales			Y: Density of Clean Vehicle Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Types	Hybrid	PEV	All Types	Hybrid	PEV
South Coast						
Treated*After	0.907***	0.509***	0.397***	0.0350***	0.0183***	0.0167***
	(0.103)	(0.084)	(0.0588)	(0.00417)	(0.00333)	(0.00243)
R-squared	0.187	0.178	0.09	0.115	0.112	0.055
Observations	17,688	17,688	17,688	17,688	17,688	17,688
Number of zip	536	536	536	536	536	536
San Joaquin Valley						
Treated*After	0.196**	0.171**	0.0255	0.0113**	0.00956***	0.00176
	(0.088)	(0.0701)	(0.0524)	(0.00447)	(0.00363)	(0.00252)
R-squared	0.113	0.121	0.042	0.066	0.07	0.022
Observations	12,837	12,837	12,837	12,837	12,837	12,837
Number of zip	389	389	389	389	389	389

only 0.196, indicating that South Coast is the major driving force behind the spillover effects.

1.4.4 Robustness checks

In this section, we present two robust checks in addition to the main results. First, we re-estimate the baseline results using an alternative control group that are more alike the treatment group in unobserved factors. Second, we run a placebo test to show the effect we found in the main specification is not a result of seasonal factors.

1.4.4.1 Synthetic control

People may argue that disadvantaged zip codes in the rest of California are different in nature from those in San Joaquin Valley and South Coast. Though they are close in the disadvantaged score, there may be unobserved factors that lead to the gap in their clean vehicle adoption behavior. Therefore, we use the synthetic control method to generate an alternative set of control group that matches the treatment group by pre-treatment clean vehicle adoption. In this way, the two groups resemble each other in the clean vehicle market, in not only the observed factors, but also the unobserved ones.[14]

We generate the synthetic control group in 3 steps. First, a linear space of control group is decided. We use the control group in the baseline specification, i.e. all disadvantaged zip codes in the rest of California, to construct the linear space. Second, for each zip code in the treatment group, we generate a linear combination on this space so that the distance is minimized between this combination and the zip code in the treatment group. Thus, the combination is the synthetic control group for that zip code. The distance between two zip codes is defined as the sum squared distance of the following variables: the clean vehicle sales per 1,000 people 1 month, 2 months, . . ., 5 months prior to the treatment, median household income, and the percentage of college+ education. Figure 1.4 depicts the trend of clean vehicle sales per 1,000 people between the two groups to show how close they are.

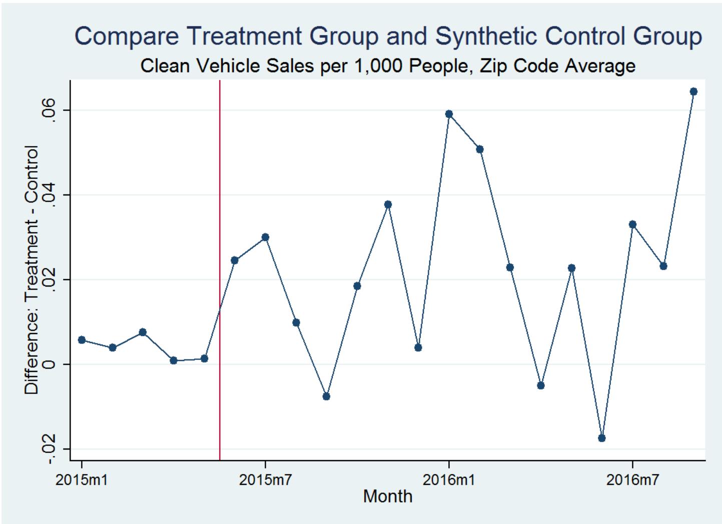

Figure 1.4: The Trend of Clean Vehicle Sales per 1,000 People Using Synthetic Control

Finally, after a synthetic control is created for each treated zip code, the average

[14]The synthetic control method is similar to p-score matching, only that it matches the dependent variable instead of explanatory variables.

treatment effect is estimated by:

$$y_{it} = \alpha + \sum_{\tau=1}^{T} \beta_\tau 1\{t = \tau\} + \sum_{m=1}^{M} \gamma_m 1\{i \in m\} + \delta D_{it} + \epsilon_{it}$$

Where y_{it} refers to the clean vehicle sales per 1,000 people in zip code i, month t. Different from the baseline regression, the zip code fixed effect here is based on the treatment-control group pair m.

Panel B of Table 1.7 reports the results for the synthetic control method. Column (4) shows an estimate of 0.0231 using the clean vehicle sales per 1,000 people as the dependent variable. It is close to the corresponding baseline estimate of 0.0268, indicating that the synthetic control method supports the main results.

1.4.4.2 Placebo test

The second robust check addresses the doubt that the results we found might be a result of seasonal fluctuations instead of treatment effect. Admittedly, clean vehicle sales have been significantly impacted by gasoline price, which is usually higher in the winter. We run a placebo test to show the effect of our months of study on clean vehicle adoption, but without the additional treatment.

In this test, we suppose there is a pseudo-treatment identical to the actual program, only that it was implemented one year prior, starting June 2014. We re-run the baseline regression function using the pseudo-event as the "treatment", and 17 months around June 2014 as the period of study. We would expect to find insignificant effects of the pseudo-treatment, suggesting that the strong impacts of the actual program are reliable in our baseline regression. Otherwise, the impacts might be a result of some uncontrolled factors, instead of EFMP & Plus-up itself.

Panel C of Table 1.7 presents the results for the placebo test. On one hand, most of these estimates are much smaller in scale compared to the baseline regression, with even negative effects on PEV sales. But on the other hand, the pseudo impacts on hybrid sales and adoption rates are too close to that of the actual subsidy, and the pseudo impacts on sales are still significant, though with lower level than the actual results. Therefore, we would suggest looking at adoption rates, instead of number of sales, in measuring the program effect, because the latter is also affected by population in the geographical unit, which is often correlated with unobserved social and economic well-beings.

1.5 Extensions: A Closer Look at Consumer Responses

The main analysis studies the average treatment effect of the program. We are also interested in the distributional effects of the program between income groups, geographical region, as well as over time.

1.5.1 The change of treatment effects over time

As the first extension, we estimate the main regression, but change the period after treatment to be 1 month, 2 months, ..., 15 months, respectively. The result with 15 months after the treatment is equivalent to the main scenario.

Figure 1.5 shows the trend of our estimates, for all clean vehicles, hybrids, and PEVs. We find that the treatment effect varies greatly depending on the period of study: the effect on hybrid purchases dipped since November 2015, while that on PEV purchases emerged around the same time. The trend reveals that, first, there may exist significant substitution effect between hybrids and PEVs in the low-income market, which explains the simultaneous movement in opposite directions. Second, the effectiveness of the EFMP & Plus-up might have been enhanced in later months by the newly-adopted income-cap policy of CVRP. But the potential interaction with CVRP cannot fully explain the evolution of treatment effects, considering PEV sales started to soar five months prior to the change in CVRP policy.[15]

1.5.2 The relationship between low income concentration and treatment effects

The baseline regression examines what types of clean vehicles people purchased as a side effect of the EFMP & Plus-up. However, it does not automatically reveal who the buyers

[15] Apart from CVRP, the treatment effect may also be affected by increasing number of available PEV models in the market around November 2015.

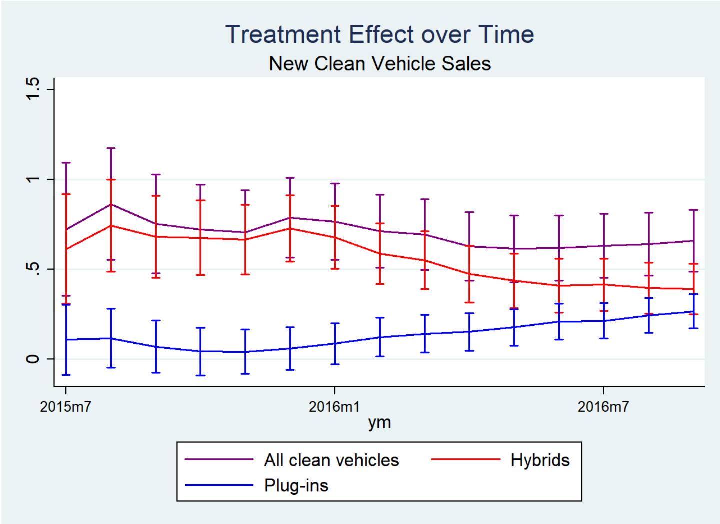

Figure 1.5: Treatment Effects of EFMP Plus-up over Time

are. We answer this question in the second extension. The objective is twofold: (1) to examine how the treatment effects we found differentiate among income groups; and (2) to see how much of the spillover effects came from of low income households that the program targeted to help, and how much of it came from higher income groups.

The test involves a triple-difference design, using the heterogeneous intensity of treatment in each zip code as the third dimension. Because the program only applies to low income households,[16] the more low-income households there are, the more intensive the program effects could be in that zip code. Hence, we proxy the treatment intensity by the percentage of low income households. The regression is:

$$y_{it} = \alpha + \sum_{\tau=1}^{T} \beta_\tau 1\{t=\tau\} + \sum_{\iota=1}^{I} \gamma_\iota 1\{i=\iota\} + \delta_1 D_{it} + \delta_2 \%\text{LowInc}_i \times \text{After}_t + \delta_3 \%\text{LowInc}_i \times D_{it} + \epsilon_{it}$$

Where $\%\text{LowInc}_i$ refers to the percentage of low income households in zip code i. Same as in the baseline regression, D_{it} is the interaction of treatment group and after treatment period, $\sum_{\tau=1}^{T} \beta_\tau 1\{t=\tau\}$ and $\sum_{\iota=1}^{I} \gamma_\iota 1\{i=\iota\}$ are the month and the zip code fixed effect. δ_3 is the coefficient of interest, reflecting how the low-income group concentration has affected the program uptake. For example, if it is mainly the higher-income group that responded to the program, then the difference-in-difference regression may report the aggregate treatment effects, but the triple-difference regression will find

[16]More precisely, eligible applicants are low income households with an old, polluting vehicle. But vehicle ownership is hard to observe in census data.

δ_3 to be smaller and less significant.

Table 1.9: Triple-Difference Regression on EFMP and Plus-up

	Y: Clean Vehicle Sales per 1,000 People					
	(1)	(2)	(3)	(4)	(5)	(6)
	All Types	Hybrid	PEV	All Types	Hybrid	PEV
Treated*After	0.0605***	0.0344**	0.0262**	0.0783***	0.0288	0.0496***
	(0.0186)	(0.0147)	(0.011)	(0.0223)	(0.0177)	(0.0132)
After*%($\leq 4 * FPL$)	-0.0203	0.0327*	-0.0529***			
	(0.0232)	(0.0184)	(0.0137)			
Treated*After*%($\leq 4 * FPL$)	-0.0610**	-0.0348	-0.0263			
	(0.028)	(0.0222)	(0.0165)			
After*%($\leq 2 * FPL$)				0.015	0.0518**	-0.0368**
				(0.027)	(0.0214)	(0.0159)
Treated*After*%($\leq 2 * FPL$)				-0.0801**	-0.0517**	-0.0284
				(0.0314)	(0.0249)	(0.0186)
After*%(2-to-4*FPL)				-0.136***	-0.0301	-0.106***
				(0.0507)	(0.0402)	(0.0299)
Treated* After*%(2-to-4*FPL)				-0.103	0.00643	-0.109***
				(0.0668)	(0.053)	(0.0394)
R-squared	0.1	0.104	0.049	0.101	0.104	0.052
Observations	14,658	14,658	14,658	14,658	14,658	14,658
Number of zip	698	698	698	698	698	698

Table 1.9 reports the triple-difference results. The outcome of interest is the clean vehicle sales per 1,000 people. The results for the first specification are reported in Column (1) to (3), where we use the percentage of households with income smaller or equal to 400% of FPL as the proxy for treatment intensity. As a comparison and robust check, income brackets are further divided into "smaller or equal to 200% of FPL" and "between 201% and 400% of FPL" in Column (4) to (6).

The choice of proxies corresponds to the three income thresholds of the EFMP & Plus-up program, where low income households are grouped into less than or equal to 225% of FPL, between 226% and 300% of FPL, and between 301% and 400% of FPL. We use the closest imitation available in ACS data set, allowing two categories of low income: less than or equal to 200% of FPL, and between 201% and 400% of FPL.

The negative estimates imply that the more income eligible households there are, the smaller the treatment effect is, keeping other factors constant.[17] Moreover, lower income does not affect hybrids adoption significantly, but are negatively correlated with the adoption of PEVs, the more expensive and advanced type of clean vehicles, under both categorization of income groups. The results indicate that, first, the bottom income bracket is not very responsive towards the subsidies campaign, which is not very surprising in light of other literature. And second, while the program specifically targets the low-income households and is highly rationed, it effectively influenced other segments of the clean vehicle market through equilibrium effect.

1.6 The Impacts on Environment and Public Health

Environmental benefits of the program come from the health and economic gain due to reduced emission, in other words, the avoided damages on human health, crops, materials, etc. In this section, we estimate the environmental benefits of EFMP & Plus-up program through direct financial transfer and through spillover effects, respectively. Although the latter is often overlooked in current studies, we show that it may bring unexpected return to the subsidy program.

1.6.1 Method

The environmental benefit is computed as the emission damage from retired vehicles minuses the damage from replacement vehicles over expected lifetime. The damages in dollar are expressed by the following equation:

$$\text{DAM}_{ij} = \$ \text{ per mile}_{ij} \times \text{miles per year}_j \times \text{lifetime}$$

Where DAM_{ij} refers to the damages in dollars related to the emission from vehicle model i in county j over lifetime. It is further expressed as the following for gasoline

[17]Noticeably, the scale of the coefficient of "Treated×After×%(2-to-4×FPL)" is much larger than the other two triple-difference terms related to the bottom income group. This could be due to the particularly small percentage of ≤2×FPL.

miles:

$$\$ \text{ per mile}_{ij} = \$ \text{ per emission}_j \times \text{emission per gallon} \times \text{gallon per mile}_i$$

Where \$ per emission$_j$ refers to the damages per unit of emission to human health, crops and materials, etc. in county j, all transformed into dollars. The number varies by county, depending on the population level, the number of buildings, crops, etc. Emission per gallon is taken from CA standards, with details for each pollutant provided in Appendix A3.

And for electricity miles:

$$\$ \text{ per mile}_i = \$ \text{ per kWh} \times \text{kWh per mile}_i$$

Where \$ per kWh calculates the damages from carbon dioxides generated by power plants. And kWh per mile is determined by the fuel efficiency of electric vehicles.

In the computation, we first decide a set of representative retired and replacement vehicles, and then estimate the lifetime damage of each vehicle model by county, using fuel efficiency for each car, and transportation and economic characteristics at county level. This allows us to compute the damage avoided by incentivizing car replacement through EFMP & Plus-up.

1.6.2 Data sources

We estimate the miles per year using the county-level median reported by 2012 California Household Travel Survey (CHTS). For example, the median driver in Los Angeles county travels 5,611 miles annually. We assume no difference in miles travelled between vehicle models within a county.

The remaining lifetime is assumed to be 10 years for all retired and replacement cars. This assumption could be strong, stating that the already-aged retired cars would be in use for another 10 years without the program, especially for direct beneficiaries of the subsidy whose old cars can date back to the 1990s. This number can be altered later if precise information is available.

For \$ per emission$_j$, emission per gallon, and \$ per emission$_j$, we take the estimates from Holland et al., (2016). Our sample covers the 12 counties in San Joaquin Valley and

South Coast. In their calculation, the damage to crop, timber and material is calculated in 2011 market prices, and the damage to human health is valued at $6 million value of statistical life (VSL).

Note that we assume 60% of PHEV miles are run on gasoline, and 40% on electricity. Besides, all hybrid miles are gasoline, and all BEV miles are electricity.

For gallon per mile$_i$ and kWh per mile$_i$, we refer to the fuel economy information provided by Department of Energy Office of Energy Efficiency & Renewable Energy and EPA.[18] For each of our retired and replacement vehicle models, we use miles per gallon (MPG) for gasoline cars, and kWh per 100 miles for electric cars. Note that the retired vehicles of directly subsidized consumers are usually around 10 years old, and thus the depreciation of fuel efficiency is not negligible. We assume that the fuel efficiency depreciates by 1% annually for both gasoline and electricity miles.[19]

For directly subsidized vehicles, we observe the retired and replacement model from the dataset of program applicants. We select the top 11[20] retired vehicle models to construct a representative model, weighted by within-program frequency, and in the same way construct a representative replacement car. The model-year is the within-program average model-year of that vehicle. Appendix A3.3 reports the choice of retired and replacement vehicles for the environmental welfare through direct transfer, as well as their fuel efficiency.

However, it is impossible to observe the actual retired and replacement cars for the spillover sales. Hence, we assume they are a representative sample from the entire market of new clean vehicles. We select the top 10 vehicles among hybrids, PHEVs and BEVs, respectively, during June 2015 and September 2016 in the treatment group, and assign a retired vehicle to each based on the manufacturer, model, body type, etc. Appendix A3.4 reports the choice of retired and replacement vehicles for the environmental welfare through spillover sales, as well as their fuel efficiency.

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[18] The official U.S. government source for fuel economy information, `https://www.fueleconomy.gov`.

[19] The estimate comes from the average annual increase in CO_2 per mile in EMFAC model, in which CO_2 per mile is assumed to be linear to the inverse of MPG and grows at 1% per year over a long time. People may argue 1) the rate of depreciation is nonlinear, or 2) CO_2 standards were different back in the 1990s. Both arguments are reasonable and can be improved with more evidence.

[20] Ties at top 10 and 11.

1.6.3 Results

Table 1.10 presents the environmental gains of EFMP & Plus-up program through direct transfer and spillover effect, respectively.

Damage reduced per car per annum

Column (1) and (3) reports the damage reduced per car per annum through direct transfer and spillover effects, by the fuel type of replacement vehicles and air district. Intuitively, BEVs are much more environmentally friendly compared to hybrids, while the benefits of turning to PHEVs may depend on how clean the alternative vehicle is. Besides, the per-car benefit is much higher among those subsidized directly than the spillover sales, with doubled or tripled gains. This is because the retired vehicles of the former group, typically gasoline cars produced in the 1990s, are the major source of on-the-road pollution due to fuel efficiency depreciation. Also, the environmental gains in South Coast are higher than in San Joaquin Valley in general, because of the larger population and more economic activities in the former region. To sum, on the per-car basis, it is much more efficient to subsidizing polluting car drivers as opposed to the general public, which is consistent with the highly rationed design of the program.

Aggregated lifetime gains

Column (2) and (4) reports the lifetime damage reduced by all sales attributed to EFMP & Plus-up program through direct transfer and spillover effects during June 2015 and September 2016, categorized by the fuel type of the replacement vehicle and air district. Because of the large number of spillover sales (approximately 5,000 cars during that period) compared to direct transfer (approximately 1,100 cars), the former dominates in aggregated environmental gains in two-region total. The dominance is driven by South Coast alone, though, because the spillover effect is found to be small and not so significant in San Joaquin Valley.

Altogether, we estimate a 5 million dollars environmental gain during the first 16 months of the program, two-thirds of which comes from social spillover effects and the rest from direct transfer to the targeted consumers.

Benefits-to-revenue ratio

The last row reports the benefits-to-revenue ratio of the program, accounting for

Table 1.10: Comparison of Environmental Gains of EFMP Plus-up Through Direct Transfer and Spillover Effect

	Subsidized vehicles		Spillover sales		**Two parts total**
	Damage reduced per car per annum ($)	Aggregated damage reduced ($)	Damage reduced per car per annum ($)	Aggregated damage reduced ($)	**Aggregated damage reduced ($)**
South Coast					
Hybrids	185.50	575,050.00	56.50	1,449,477.10	
PHEVs	215.49	415,895.70	40.72	419,988.91	
BEVs	273.28	352,531.20	103.21	1,000,598.80	
Total		$1,343,476.90		$2,870,064.81	
San Joaquin Valley					
Hybrids	112.63	314,237.70	45.93	211,138.11	
PHEVs	120.29	190,058.20	20.05	-	
BEVs	143.31	123,246.60	56.93	-	
Total		$627,542.50		$211,138.11	
Two regions total		**$1,971,019.40**		**$3,081,202.92**	**$5,052,222.32**
Benefits-to-revenue ratio		**19.2%**		**30.1%**	**49.3%**

Note: (1) Aggregated damage reduced equals to Damage reduced per car per annum times 10 times vehicle sales (through the program or estimated spillover) during June 2015 to September 2016, assuming 10 years lifetime for each vehicle, and that the marginal effect on BEV or PHEV is proportional to their sales. (2) Benefit-to-revenue ratio equals to Aggregated damage reduced divided by Subsidies spent during June 2015 and September 2016. The amount of subsidies, approximately $10 million, is provided by the program's applicants information.

public health and economic gains alone. The ratio equals to the aggregated lifetime environmental gains, either through direct transfer, through spillover, or both, divided by the total subsidy transfer amount during the period. The total transfer is computed from the program data set of successful applicants. From June 2015 to September 2016, there are approximately 10.25 million dollars in total subsidized to consumers through EFMP & Plus-up program. Environmental gains from these directly subsidized vehicles make up 19.2% of the investment, and those from spillover sales bring 30.1% in return. In summation, nearly 50% of the financial transfer are passed through to public health and environment.

1.7 Conclusion

Policies may have a specific target, but the impact may spread to a much larger audience through the market equilibrium. Thus, the welfare consequences of a program may be incomplete if the spillover effects are not considered.

In this paper, we study a subsidy program that focus on the bottom income group who switch from old, polluting cars to clean energy vehicles. Although a large portion of the successful applicants bought clean vehicles from the used car market, we find the new clean vehicle market was affected as well. Using a difference-in-difference regression, we show that there was an increase of 10% in new clean vehicle adoption rate. The results were mainly driven by South Coast air district, where the publication campaign was compared to San Joaquin Valley. All three types of clean vehicles, hybrids, PHEVs and BEVs, were positively affected, though hybrid buyers responded immediately while plug-in buyers waited for around six months to respond. Also, we find that as a result of the program, it is the higher income group that purchased additional clean vehicles in the new car market.

Regarding the environmental welfare, from June 2015 to September 2016, the program has generated approximately 1.97 million dollars through direct financial transfer, and 3.08 million dollars through spillover effects in lifetime environmental benefits, adding up to 49.3% of the program's investment.

Although the subsidy program is highly-rationed, it still affected other segments of the clean vehicle market through market equilibrium, network, or information spread. Hence, it is important to take into account these spillover effects when evaluating the government-sponsored program.

CHAPTER 2

Green Dollars: The Impact of Clean Vehicle Subsidies

2.1 Introduction

Are government clean vehicle subsidies useful in increasing sales? Who are benefiting from the subsidies? This paper aims to answer the two questions.

Clean vehicle market is a textbook example for positive externalities. When a consumer buys a clean vehicle, his willingness to pay is associated with the level of private benefits but not social welfare brought by producing fewer emissions. Hence, the government acts to internalize that social welfare by providing monetary incentives so that the consumer willingness to pay includes both private and social welfare. However, it is not that simple to decide the amount of subsidy for two major reasons. First of all, there are very few studies quantifying the average amount of social welfare and cost associated with one clean vehicle, and that amount can vary across states, according to a study by Holland, Mansur, Muller and Yates (2016). Besides, it is unclear how to distribute the subsidy when consumers have heterogeneous demand curves. This paper aims to solve the second problem in three steps. First, I show reduced-form evidence that there are variations in the demand curve of clean vehicles, depending on vehicle types and consumer income level. Therefore, it is reasonable to consider heterogeneity in elasticity of different income groups. Next, I quantify the price elasticity of demand for each clean vehicle type by estimating a market equilibrium model. After that, I use the estimated price elasticity to show how many clean vehicle sales can be attributed to current subsidies in the period of study.

The market for clean vehicle has experienced rapid growth in the 21st century. Hybrids were introduced earlier than the plug-ins. The first models sold in the U.S. are Toyota

Prius and Honda Insight in 2000. In 2015, there are 104,499 new hybrids sold in California, representing 5.1% of total new vehicle sales in the state. Plug-in hybrids (PHEVs) and Battery-only electric cars (BEVs) entered the market around 2010. In California, PHEV sales grow from 97 in 2010 to 29,949 in 2014, representing 1.6% of total vehicle sales that year. BEVs outsold PHEVs in 2013, partly thanks to the popularity of Tesla. Up to March 2016, California has contributed almost half of the PHEV and BEV sales in the country. The state is projected to witness over 1.5 million zero-emission vehicles on roads, including PHEVs and BEVs, by 2025. The introduction of environmentally-friendly vehicle models not only emits fewer gases, but also saves more fuel costs for the consumers. To stimulate sales, the government has provided considerable amount of subsidies to clean vehicle buyers. For example, the Federal government now offers up to $7,500 tax rebate to BEV buyers and around $4,000 to PHEV buyers. The California state offers up to $4,000 in cash to BEV buyers and up to $3,000 to PHEV buyers through CVRP program. Other states and local governments also have their rebate designs. But to conclude, most of the current subsidies are provided to PHEV and BEV buyers, not traditional hybrids consumers.

This paper makes three contributions. First, I provide reduced-form results on the evaluation of two clean vehicle subsidy programs in California. The first program aims at helping consumers in the disadvantaged communities to buy fuel-efficient vehicles, especially those from low income households. Eligible vehicles include all hybrids, PHEVs and BEVs, and both new and used car purchases. The lowest income households who buy the cleanest vehicles receive the highest level of subsidies. The amount of subsidy can reach as high as $9,500. Compared to other programs, it has the feature that the rebate is transferred to the dealership account at the time of purchase, or only a few days later, so that the rebate can help low income consumers pay off the down payment directly. Using the geographical coverage and the timing of implementation of the program, I conclude that low income households indeed respond to the monetary incentives by buying more clean vehicles. However, most of the effects are captured by hybrid sales, while PHEV and BEV sales were not influenced significantly. The result is consistent with intuitions: people should buy more clean vehicles in response to the program. Moreover, they are likely to buy the cheapest models, largely coincide with hybrid models, due to the budget constraint.

The second program refers to California Clean Vehicle Rebate Project (CVRP). It started in March 2010 and just changed its rebate scheme in March 2016. Previously, it adopted a flat rate scheme for all applicants, with $\$2,500$ for BEV buyers and $\$1,500$ for PHEV buyers. After the change, applicants exceeding an income cap will no longer get any money back; in contrast, low income applicants will receive more. It applies to new car purchases only. Using the variations in income distribution across zip code level markets, I show that low income households are not significantly encouraged by the policy change, while the high income group responds by buying fewer PHEVs and BEVs. Though a little bit disappointed, it is not very surprising to find the low income not responding, considering the PHEV and BEV results regarding the first program. To summarize, the effect of government subsidies varies, and is dependent on vehicle and income eligibility requirements, as well as income distribution in the local market.

However, it is difficult to measure the marginal effect of subsidies for each income category with the reduced-form results alone. There are multiple reasons for this. First, the amount of subsidies and the income eligibility is not the same in various programs. For example, a program with $\$1,000$ rebate may be found not useful, while another program giving $\$5,000$ rebate may increase the sales. In this case, reduced-form estimates can be contradictory to each other. Besides, response from the suppliers has been left aside in the previous analysis, which means the direct effect of subsidies and its indirect effect through pricing decisions are mixed together. Hence, I cannot tell if it is the potential buyers not responding to monetary incentives, or it is the benefits fully offset by pricing increases when producers fully anticipate the subsidies.

As a result, I make the second contribution by developing and estimating a static market equilibrium model of the clean vehicle market. The model is based on the reduced-form results. It captures the vehicle choices of households with different income level and preferences, and the pricing decisions of the profit maximizing suppliers.

On the demand side, each household chooses one vehicle to purchase. They can buy either a new car or a used one. No matter new or used, I nest the vehicles from two dimensions: (1) luxury or non-luxury; and (2) hybrids, PHEVs and BEVs, or conventional gasoline cars. Hence, the household is making a discrete choice among altogether

12 options. The utility can come from two sources: driving the car, and other consumption. The more the vehicle is driven, the more utility it brings. The actual mileage is not observed, and thus will be calculated using first order conditions and be plugged in to get the indirect utility functions. The household then spends all money left on other consumption after paying for the vehicle price and fuel cost. Households from different income categories are allowed to have different levels of marginal utility on other consumption. The model is constructed in a static setting, assuming that each household makes only one purchase in the lifetime and does not resell, and that the timing of purchase is unimportant.

On the supply side, producers play a Bertrand game and decide optimal prices. Each producer maximizes its total profit, which is decided by vehicle price, marginal cost of production, and market share of the vehicle. In the model, I assume that there is only one producer in each market. By "producer" I mean more of the dealership than of the factory. In each community, the dealership chooses how many cars to subscribe from the factory, and how much to charge the consumers. It hereby works as a local producer. In equilibrium, consumer choices and pricing strategies jointly form the transaction prices and market shares of vehicles.

The model is estimated using a random coefficient logit model. The predicted value for market shares and transaction prices matches well with the observation. It simulates the pattern of vehicle market shares within a market, and also the variation between markets with different demographics. In the model, the difference in the market shares is generated by vehicle characteristics, the distribution of demographics, and their interactions. When a clean vehicle rebate aiming at a specific income group is introduced, buyers from that group can enjoy more other consumption after paying for it, and thus are likely to contribute to higher market shares. Although this will result in higher absolute values of the own-price elasticity considering that the current market share of clean vehicles is relatively low, the direct effect of increasing market shares still outweighs this indirect effect, leading to higher markups and hence higher transaction prices. This in turn prevents the market shares from growing too much. As a result, the equilibrium market shares reflect the marginal utility on other consumption of that income group, as well as the value of the price elasticity of eligible clean vehicles.

The third contribution I make is applying the model to simulate the impact of counter-factual subsidy designs. The difficulty is that both market shares and transaction prices may change in response to subsidies. Thus, I use an iteration process to numerically solve for the new market shares and prices simultaneously. I study two policy designs: 1) Assume CVRP further reduces its income cap to 500% Federal Poverty Line and increases the low income subsidy to $\$5,000$ for PHEVs and $\$6,000$ to BEVs. This design is a closer mimic of the experimental EFMP Plus-up program implemented in parts of California. 2) Assume the federal tax credit sets an income cap at $\$500,000$ for households. Both counter-factual cases thrive to design a more progressive type of incentive.

This research is built on the BLP framework to estimate demand for differentiated products in a static market equilibrium model. This framework has been traditionally used to analyze a wide range of markets including automobile. This paper emphasize the variation in demand elasticity between income groups and between vehicles of various fuel types.

This paper also contributes to the literature on estimating price elasticity of demand for PHEVs and BEVs. The market is relatively new, and its market share has been too small to analyze until recently in California. Beresteanu and Li (2011) has studied the role of subsidies for hybrids. But the difference between plug-in vehicles, i.e. PHEVs and BEVs, and hybrids might be even larger than that between hybrids and gasoline cars, from the users perspective. Thus, separate analyses are still needed.

The rest of the paper will proceed as follows: Section 2 introduces and summarizes available data sets; Section 3 shows reduced-form evidence on the impact of subsidies; Section 4 develops a static market equilibrium model; Section 5 explains the instruments and estimation procedures; Section 6 interprets the results from estimation; and finally Section 7 simulates counter-factual policy consequences.

2.2 Data

In this section I describe the important data sets used in the analyses. Vehicle sales, prices, characteristics, as well as market demographics are used to construct vehicle-county-quarter level observations.

2.2.1 Vehicle registrations

The vehicle registration data consists of two parts. The first is from CrossSell with new car registrations on model-zip code-month level. However, quite a few clean vehicles are distinguished from gasoline cars only on the submodel level. For example, sales of Honda Accord hybrid are included in the sales of regular Honda Accords. Therefore, I combine this data with a specific clean vehicle registration data set from Polk to separate sales of hybrid, PHEV and BEV submodels. The period of study is July 2015 to June 2016, since this is a relatively stable period of the emerging market for PHEVs and BEVs, which began around 2010 and grew rapidly during oil price peaks, and includes an exogenous change of the clean vehicle rebate program in California. A very small fraction (around 2%) of registrations come from out-of-state purchases, trucks and buses, and dealership sales, and is excluded from our sample. Figure 2.1 shows the trend of new vehicle registrations in California by fuel type. Each quarter clean vehicles takes up around 7% of total registrations, with hybrids being the majority but PHEVs and BEVs catching up in 2016Q2. PHEVs and BEVs also tend to have higher sales in the winter, when gas price is higher in general, although the variation is much smaller than the fluctuations in gasoline cars.

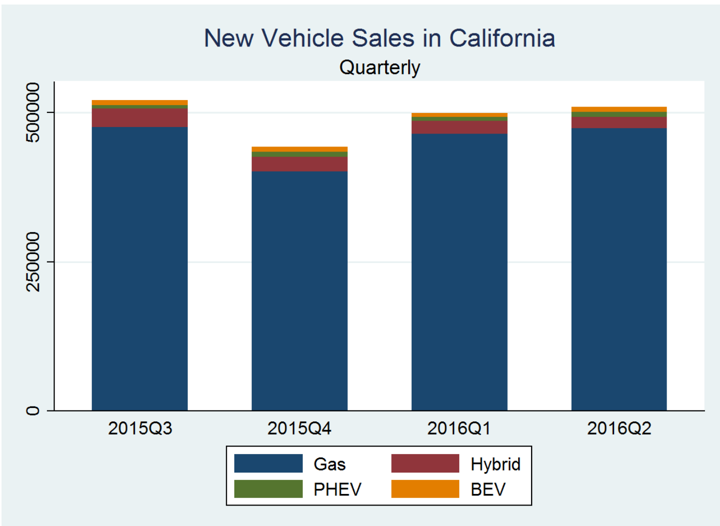

Figure 2.1: Fuel Type of New Vehicle Sales in California

It is worth mentioning that I do not consider endogenous choice set problem. It is likely that the vehicles at dealerships in different areas are different and incomplete subsets of all models available in the U.S. market, but it is unobservable in the data. I do consider that there are a few 2016 new models not introduced to the U.S. market until later in my study period. The quarter of entering the market is decided by Google news and Wikipedia. The number of newly-introduced models is so small that it does not affect the market structure much. Many 2015 models are continued in 2016, whose change in characteristics is ignored in this paper. Table 2.1 exhibits the number of available models in California by quarter and fuel type.

Table 2.1: Number of Vehicle Models Available by Fuel

	2015Q3	**2015Q4**	**2016Q1**	**2016Q2**
Gasoline cars	239	239	240	246
Hybrids	37	37	37	37
PHEVs	16	16	18	18
BEVs	13	13	13	13

I use county as the geographical unit, because it is large enough to be segregated, and still small enough to keep track of demographic variations. Each county-quarter is taken as a separate market in a static setting, assuming that vehicle demand in each county are not correlated between quarters.

This sales data provides me with the variable of market share and conditional market share. Taking the number of households in each county as market size, the unconditional market share, or just referred to as market share, is defined as vehicle sales divided by market size. The conditional market share, share of the vehicle conditional on buying, is defined as the vehicle sales divided by total quarterly sales in that county. Table 2.2 presents the average market share per vehicle by quarter and fuel type.

2.2.2 Transaction prices

The price data I use is scrapped from TrueCar, one of the largest online car dealer website. For each model the monthly trend of average transaction prices is reported after inputting the zip code. Besides, the price varies between submodels with different fuel types. Hence, I download monthly prices at zip code level for each vehicle, and calculate the county-quarter average.

Table 2.2: Vehicle Market Shares by Fuel

	2015Q3	2015Q4	2016Q1	2016Q2
Market share				
Gasoline cars	0.0111%	0.0091%	0.0101%	0.0102%
Hybrids	0.0041%	0.0033%	0.0029%	0.0027%
PHEVs	0.0018%	0.0024%	0.0016%	0.0018%
BEVs	0.0027%	0.0028%	0.0022%	0.0032%
Conditional market share				
Gasoline cars	0.3884%	0.3854%	0.3908%	0.3808%
Hybrids	0.1396%	0.1383%	0.1139%	0.1035%
PHEVs	0.0596%	0.0917%	0.0573%	0.0619%
BEVs	0.0810%	0.1011%	0.0735%	0.1059%

Two measures are reported by the website: market average price and TrueCar estimate. The market average price is supposed to be average transaction prices from dealership within 50-mile radius of the zip code. TrueCar estimate integrates the company's knowledge about consumer interest and dealership information, but the method is unknown. The two measures usually have similar trends, but may differ in the amount.

The reason I use this web scrapping source is that subsidizing consumers may affect market equilibrium through pricing, but micro-level transaction prices are not included in my data sets. Unlike BLP and some of the other studies that used MSRP, my study has a short time span of four quarters, and would not be sufficient for MSRP to respond to consumer subsidies. Table 2.3 shows an example of how this data offers more variation than MSRP in vehicle pricing both across counties and quarters. It shows the transaction price of Toyota RAV4 in a few counties by quarter, for which the MSRP is $\$27,790$ with the most popular style and options. Some of the measures lack variation, as 2015Q4 in this case, due to either the original uniform data from the website or the way I treat missing variables. But still, a lot more information is provided compared to using MSRP across county and over time. The discount rate between transaction price and MSRP also indicates intensity of market demand.

Table 2.3: Example: Transaction Prices of Toyota RAV4 by County and Quarter

	2015Q3	**2015Q4**	**2016Q1**	**2016Q2**
Los Angeles	26,298.52	26,715.33	26,202.38	26,215.67
San Diego	26,241.31	26,715.33	26,198.63	26,210.67
Orange	26,319.79	26,715.33	26,202.38	26,215.67
San Bernardino	26,344.59	26,715.33	26,202.38	26,215.67
Sacramento	26,242.29	26,715.33	26,188.88	26,198.17
San Joaquin	26,273.56	26,715.33	26,188.88	26,198.17

Missing data may be a result of too few sales. I follow the procedures below to fix the problem:

Step 1. For a county-quarter-vehicle combination, transaction price is defined as market average price if it is not missing.

Step 2. For such a combination, if market average price is missing but TrueCar estimate is available, then I recover the market average price from TrueCar estimate using a discount rate. The rate is the average discount rate of that county-vehicle if there is at least one non-missing observation in the market. If all observations miss data within that county-vehicle group, then I turn to the quarter-vehicle in surrounding counties for discount rate. If that still does not work, then the discount rate can be derived from quarter-vehicle observations of all other counties.

Step 3. If both measures are missing, then I look for the MSRP for the most popular styles and options on TrueCar website, and recover market average price using discount rate with respect to MSRP. The process of deciding the appropriate discount rate is similar to Step 2.

2.2.3 Vehicle characteristics

Vehicle characteristics other than price affect market shares through consumer utility function. Factors that come into utility function directly are either financial or non-financial. Financial factor refers to cost per 100 miles, and non-financial factors include total range with a full tank, as well as indicators for luxury brand, hybrid, PHEV and

BEV. All the non-financial factors other than luxury can be found on the FuelEconomy website of DOE. Luxury vehicles are decided by Google the vehicle information. Below is a list of brands that most of whose vehicles are luxurious:

Brands with all vehicles defined as luxury: BMW, Mercedes-Benz, Tesla, Ferrari, Lexus, Porsche, Cadillac, Aston Martin, Bentley, Jaguar, Infiniti, Acura, Land Rover, Lincoln, Maserati, Volvo

Brands with at least one high-end luxury models: Audi, Ford, Hyundai, Kia, Nissan, Toyota, Volkswagen

Cost per 100 miles is calculated from fuel economy and gasoline or electricity prices. Fuel economy measures, i.e. MPG for gasoline cars, hybrids and PHEVs, and kWh per 100 miles for PHEVs and BEVs, also come from FuelEconomy website. In this calculation, it is assumed that PHEVs are fueled by 40% electricity and 60% gas.

Table 2.4 shows summary statistics for all vehicle characteristics by fuel type. Hybrids in general have higher range than gasoline cars because of higher MPG. PHEVs work in the same way as hybrids when fueled by gasoline and thus also have high total ranges, but their electricity range is usually between 10-40 miles. The more a vehicle relies on gas, the higher its cost per 100 miles will be. This is because gas price is generally higher than electricity price at public electric vehicle supply equipment (EVSE).

Table 2.4: Vehicle Summary Statistics by Fuel

	Gasoline	**Hybrid**	**PHEV**	**BEV**
Number of models	246	38	18	13
Transaction price ($)	46,394.73	44,584.45	61,343.11	45,499.43
$ per 100 miles	13.72	8.92	6.54	2.88
Total range	352.53	522.45	438.89	111.46
Luxury	0.48	0.50	0.67	0.31

2.2.4 Demographics and fuel cost

County-level variables enter consumer utility function in three ways. First, county-quarter level gas price and charging cost are used to calculate driving cost per 100 miles. Second, household income and travel time to work lead to heterogeneous marginal utility associated with vehicle characteristics. And third, household income and size jointly decide the amount of clean vehicle rebate from CVRP.

Household size, income and travel time to work come from ACS 2015 5-yr data from FactFinder. I collect median income and average travel time to work by county and by household size. County-quarter level gas prices, including regular, mid, premium and diesel, come from Polk for all California counties belong to metropolitan areas. Regular, mid and premium always trend together, with regular be the cheapest and premium the most expensive. I use the price of mid to calculate driving cost, and use the California quarterly average as prices in counties not included in the data. Cost of EVSE comes from a mobile app that keeps track of charging stations of major networks. From the creation date and cost per kWh of each charging station, I estimate the average cost of charging per kWh in

each county-quarter. It is possible that PHEV and BEV drivers also charge at home during the night, but the unit cost is also very low compared to gas prices. Table 2.5 shows the summary statistics for county-level variables, with fuel cost be the average over time.

2.3 Reduced-form Evidence

In this section I show empirical evidence on the impact of subsidies on clean vehicle sales and prices by analyzing two recent rebate programs in California. The reason that I analyze both programs is that they are different in the target market, vehicle eligible conditions, and average amount of subsidy per car. The difference offers great variation for the study of consumer responses. They are also comparable to each other: both are in California, and are implemented consequently in 2015 and 2016, a period with relatively stable economic environment. Combined together, they provide a complete view of government subsidies.

Table 2.5: Demographics and Fuel Price by County

County	Travel time to work (min)	Number of households	Median HH income ($)	Gas price ($/gal)	Charging price ($/kWh)	County	Travel time to work (min)	Number of households	Median HH income ($)	Gas price ($/gal)	Charging price ($/kWh)
Alameda	28.01	558,907	79,438.31	2.73	0.26	Placer	26.83	135,456	76,340.80	2.59	0.10
Butte	19.47	85,318	45,285.69	2.53	0.00	Plumas	25.30	8,217	46,661.41	2.53	0.00
Calaveras	25.30	18,060	57,290.41	2.58	0.00	Riverside	32.22	699,232	57,757.25	2.96	0.12
Colusa	25.30	6,966	51,716.06	2.59	0.00	Sacramento	25.77	522,596	57,741.84	2.59	0.08
Contra Costa	32.50	384,646	83,910.83	2.86	0.22	San Benito	25.30	17,198	71,688.59	2.73	0.17
Del Norte	25.30	9,420	41,697.22	2.67	0.00	San Bernardino	30.13	614,325	54,438.28	2.96	0.17
El Dorado	28.64	67,086	72,640.48	2.59	0.01	San Diego	24.34	1,094,157	66,748.19	2.98	0.35
Fresno	21.55	296,305	46,545.58	2.66	0.10	San Francisco	29.48	353,287	84,650.01	2.86	0.14
Glenn	25.30	9,497	41,951.10	2.53	0.00	San Joaquin	30.27	219,073	54,346.67	2.58	0.21
Humboldt	17.34	53,036	43,179.82	2.67	0.01	San Luis Obispo	21.45	103,576	63,593.45	3.02	0.01
Imperial	22.19	46,452	41,781.63	2.96	0.00	San Mateo	24.62	259,711	97,712.32	2.86	0.15
Inyo	25.30	7,957	53,161.50	2.96	0.00	Santa Barbara	18.96	142,713	65,903.75	2.93	0.09
Kern	23.22	259,700	49,607.27	2.79	0.03	Santa Clara	25.39	621,463	98,625.96	2.73	0.10
Kings	21.10	41,554	47,978.25	2.61	0.00	Santa Cruz	25.86	94,802	68,875.13	2.69	0.20
Lake	25.30	26,993	39,607.27	2.66	0.00	Shasta	19.76	69,375	46,552.72	2.67	0.06
Los Angeles	28.96	3,263,069	57,335.02	3.01	0.18	Sierra	25.30	19,133	38,433.69	2.67	0.00
Madera	25.46	43,159	45,100.43	2.66	0.00	Solano	29.52	143,612	69,803.22	2.66	0.15
Marin	26.88	103,670	99,858.09	2.86	0.24	Sonoma	24.87	187,782	67,188.56	2.73	0.12
Mariposa	25.30	7,345	51,416.48	2.65	0.00	Stanislaus	27.18	169,196	50,860.67	2.52	0.01
Mendocino	25.30	34,017	45,641.38	2.73	0.00	Sutter	25.30	31,917	52,480.12	2.52	0.00
Merced	27.13	77,692	43,614.02	2.65	0.31	Tehama	25.30	23,704	42,546.41	2.67	0.00
Mono	25.30	4,906	62,777.80	2.66	0.00	Tulare	22.95	133,570	42,728.87	2.61	0.20
Monterey	25.30	125,402	59,696.64	2.72	0.11	Ventura	25.43	268,969	79,023.63	2.99	0.26
Napa	23.86	49,494	71,565.52	2.66	0.06	Yolo	22.43	71,997	57,376.46	2.59	0.12
Nevada	25.30	40,993	59,138.66	2.59	0.00	Yuba	25.30	25,139	48,117.89	2.52	0.00
Orange	26.31	1,009,353	78,490.95	2.99	0.21						

2.3.1 Evidence on heterogeneous responses from low income and high income consumers

I start with showing evidence that high income and low income consumers may react differently towards monetary incentives. I conduct the analysis by studying CVRP, the statewide subsidy program in California, which has recently changed its rebate scheme to the low income and high income groups.

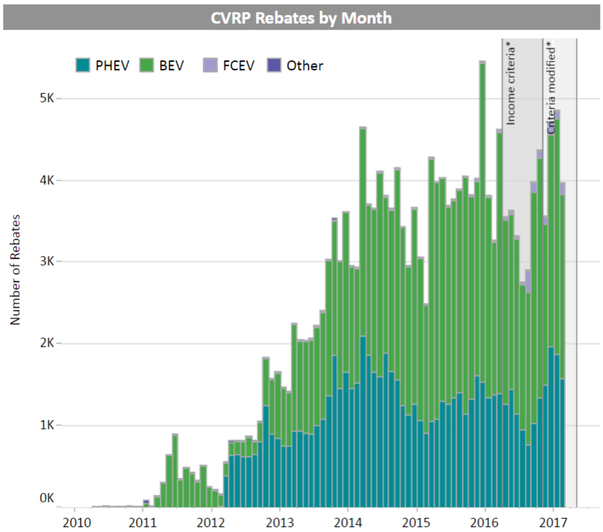

Figure 2.2: Trend of CVRP Applications by Month

CVRP has been offering rebates to clean vehicle consumers in California ever since the emergence of the market. The first claim from a battery-only electric vehicle (BEV) owner was made in January 2011. The program then extended its span of support to plug-in hybrids (PHEVs) in March 2012. According to my data, over 80% of new BEV and PHEV buyers applied to and received funding from the program, showing that it is widely utilized by the target market. In an online survey conducted by the CVRP website, 74% of the applicants claimed that the CVRP rebate is a "very important" or "extremely important" factor driving their purchase, even slightly outperforming the generous federal tax rebate which gets 71%. Up to now, the program has issued rebates to 157,333 vehicles and spent $335, 499, 185. Among these vehicles, 59.4% are BEVs and 40% are PHEVs. Figure 2.2 compares the time trend of clean vehicle registration and applications on the CVRP website. It is clear that both numbers increased rapidly since 2012, but do not resemble each other exactly month-by-month. The gap is a result of the time lag between purchase and application especially for Tesla buyers, since the policy is such that Tesla buyers can apply for rebate after subscription, while all other cars are eligible only after the contract of purchase is signed.

The rebate scheme of CVRP was changed from flat rate to a progressive type at the end of March 2016. Before that, all PHEV buyers receive $1,500, and all BEV buyers receive $2,500. After the change, buyers exceeding an income cap no longer receive any rebate, while buyers with income lower than 3 times federal poverty line are given a higher amount per car, with $4,000 for BEVs and $3,000 for PHEVs. The income cap is $250,000 for individual buyers, $340,000 for head of households, and $500,000 for joint buyers. Clean vehicles purchased after March 25th, 2016, or Tesla subscribed after that date, must follow the new scheme. Unfortunately, the program run out of funding in June and has not yet resumed. All applicants after that are put on a waiting list. Hence, my period of study starts from January 2016, and ends on June 2016. I take the program change as the policy to study, and use variations in the intensity of the policy in each zip code to identify its impact on low income and high income clean vehicle buyers, respectively.

Since the policy affects clean vehicle buyers exceeding the income cap and those whose incomes are lower than the low income threshold, the more these consumers there are in a zip code, the more the zip code is affected by the policy. Therefore, I take the percentage of low income consumers and the percentage of high income consumers to indicate the intensity of the policy on that zip code. I develop a model using difference-in-difference method:

$$y_{it} = \alpha + \sum_{\tau=1}^{T} \beta_\tau \mathbf{1}\{t=\tau\} + \sum_{\iota=1}^{I} \gamma_\iota \mathbf{1}\{i=\iota\} + \delta_1 \text{LowInc\%}_i * \text{After}_t + \delta_2 \text{HighInc\%}_i * \text{After}_t + \epsilon_{it}$$

In the regression, i represents the zip code, and t represents the month of observation. The dependent variable, y_{it}, refers to the plug-in vehicle sales excluding Tesla in zip code i month t. The reason to exclude Tesla sales is that there usually exists a few months time lag between subscription and delivery, so the timing of actual purchase does not represent the timing of applying for the rebate. For example, a Tesla registered in April is very likely to have received the CVRP funding in early March, and thus not affected by the change in rebate.

The parameters of interest are δ_1 and δ_2. δ_1 is an analog of demand elasticity of the low income group, and δ_2 corresponds to the high income group that exceeds income cap in the new CVRP.

Table 2.6 shows the parameter estimates. Column (1) represents the main result, using plug-in vehicle sales excluding Tesla as the dependent variable. Sales did decrease as the income cap is applied, but did not respond to additional subsidy for the low income group. This is probably because CVRP has not been very appealing to the low income group, with its restriction on new cars only. Column (2) reveals the potential substitution effect between plug-ins and hybrids by replacing the dependent variable with hybrid sales. The program itself does not issue rebates to hybrids, however, potential high income plug-in buyers turn to hybrids when their rebates are canceled.

Table 2.6: Effect of CVRP Change on Clean Vehicle Adoption

VARIABLES	(1) Plug-in Jan-Jun 2016 FE	(2) Hybrid Jan-Jun 2016 FE
LowInc%*After	0.116	0.559
	(0.308)	(0.459)
HighInc%*After	-1.718**	2.105**
	(0.681)	(1.015)
Time dummies	y	y
Observations	20,616	20,616
R-squared	0.087	0.14
Number of zip	1,204	1,204

2.3.2 More evidence on the responses from low income consumers

To further investigate the reactions of low income consumers, I turn to another program, the EFMP Plus-up, a pilot program implemented in part of California. It is specifically designed for the low income group, and covers a wider range of eligible vehicles compared to CVRP. The goal is to help low income households living in disadvantaged communities to buy clean vehicles. It has several features. First, it only applies to low income households, so it is suitable for studying the response of the low income group to clean vehicle subsidies. The income cap is 400% Federal Poverty Line (FPL). Secondly, consistent with its goal to help the poor, the program covers all kinds of clean vehicles, including hybrids, PHEVs and BEVs. It also accepts applications from used car buyers as well as new car buyers. Thirdly, the average amount of subsidy per car is much higher than other subsidy programs. And lastly, it is focused on the disadvantaged communities that suffer from high pollutant levels.

Using the geographical coverage and timing of the program, I estimate its effect by difference-in-difference method:

$$y_{it} = \alpha + \sum_{\tau=1}^{T} \beta_\tau \mathbf{1}\{t = \tau\} + \sum_{\iota=1}^{I} \gamma_\iota \mathbf{1}\{i = \iota\} + \delta D_{it} + \epsilon_{it}$$

D_{it} is the interaction term between the treatment group and after-treatment dummy. The parameter of interest is δ. Time fixed effects and zip code fixed effects are controlled by the second and third term on the right hand side. The purpose is to exclude any impact from common time trend or time-invariant characteristics on the zip code level.

The key assumption of the method is that the treatment group and control group trend together in clean vehicle sales without the program. As shown in the previous chapter, the clean vehicle stock in the treatment group and the control group trended together for a long period before the treatment, and diverged soon after that. The stock is defined as accumulated sales since 2010 to the current month. In other words, monthly sales equals to the slope of the stock curve.

The main results are presented in the previous chapter. The sales of both hybrids and plug-ins experienced statistical significant increase after EFMP Plus-up rebate is applied, indicating that the low income group respond towards financial incentives, but may need much larger scale of subsidy than provided in CVRP for the impact to be significant.

Combining the evidence above, I conclude that the effect of clean vehicle subsidies on consumer adoption is significant, but varies by income group and by vehicle fuel type.

Table 2.7: Effect of CVRP Change on Clean Vehicle Prices

	(1)
	Plug-in Prices
	Jan-Jun 2016
VARIABLES	FE
LowInc%*After	126.3***
	(24.40)
HighInc%*After	60.52
	(56.61)
Time dummies	y
Observations	10,672
Number of zip	1,334

2.3.3 Evidence on the impacts on transaction price

The final piece of reduced-form evidence shed light on the influences of subsidies on transaction prices. In other words, do suppliers charge more when they learn that the consumers are eligible for some rebate? The question makes sense because the dealership can actually do first degree discrimination in the bargain. The only exception is Tesla, whose prices are fixed given the style and options of a car. I use the CVRP experiment and adopt a similar approach as in the first part of this section. The intuition is that the more low income and high income households the zip code has, the more intensive transaction prices are affected by the change of CVRP subsidies.

$$p_{it} = \alpha + \sum_{\tau=1}^{T} \beta_\tau \mathbf{1}\{t=\tau\} + \sum_{\iota=1}^{I} \gamma_\iota \mathbf{1}\{i=\iota\} + \delta_1 \text{LowInc\%}_i * \text{After}_t + \delta_2 \text{HighInc\%}_i * \text{After}_t + \epsilon_{it}$$

Table 2.7 presents the estimates for the parameter of interest, δ_1 and δ_2. Although the new CVRP did not encourage more low income households to enter the market, it did affect the transaction prices on their actual purchases: around 10% of the increased rebate was transferred to the supply side. Meanwhile the transaction prices for the high income group was not changed, probably because those with lower willingness-to-pay simply exit the market.

2.4 Model

In this section I describe a static market equilibrium model that captures the key empirical facts from the reduced-form part, and explains household decision on clean vehicle purchase. There are three reasons why such a model is necessary. First, the previous section have looked at the effect of a government subsidy change on clean vehicle sales. With the model, it will be possible to estimate the price elasticity for different income groups. Second, the model will allow me to consider the reactions of the supply side to such subsidies. For example, the transaction price offered may be higher when subsidies increase. Finally, this model will enable an counter-factual analysis of simulated policy consequences.

I begin with consumer choice, and then pricing decisions of suppliers.

2.4.1 The demand side

2.4.1.1 Utility function

For household i in market m who buys vehicle j, the level of utility is:

$$u_{ijm} = \delta_{jm} + \mu_{ijm} + \epsilon_{ijm}$$

where

$$\delta_{jm} = X_{jm}\bar{\beta} + \xi_{jm}$$

$$\mu_{ijm} = \alpha\frac{p_{jm} - r_{ijm}}{y_i} + \lambda \ln(t_i) + \ln(y_i) X_{jm}\tilde{\beta}$$

and

$$X_{jm} = (1, \$/100\text{miles}_{jm}, \text{Range}_j, \text{Luxury}_j, \text{Hybrid}_j, \text{PHEV}_j, \text{BEV}_j)$$

Vehicle characteristics affect utility level in two ways: financial and non-financial. Financial channels include out-of-pocket cost $\frac{p_{jm}-r_{ijm}}{y_i}$ and cost per 100 miles, where p is transaction price, r is rebate from CVRP, and y is household income. I use the ratio of $(p-r)$ to y to denote the financial burden. The idea is that the higher the cost is relative to income, the higher the financial burden is perceived. I choose it over other measures, for example $\ln(y+r-p)$, because car buyers usually finance the purchase with a loan and thus $(p-r)$ is not necessarily smaller than their annual income, which is the case for bottom percentile income households. Hence, the ratio usually works better in estimation. The measure is also used in BLP (1999). Cost per 100 miles is decided by the fuel economy of vehicle j and fuel cost in market m.

Non-financially, vehicle characteristics including range with a full tank, whether it is luxury and fuel type affect the pleasure from driving. Specifically, I include indicators for fuel type, hybrid, PHEV and BEV, in the utility function to estimate consumer taste for these characteristics after cost of driving, range, and transaction price are controlled. Such non-financial features may include the preference for environmentally-friendly self-image; the way the electric engine starts which feels different from ICE; free access to HOV lanes; the need to park a PHEV or BEV at a charging station (and maybe to come back in a few hours to move it so no additional charge occurs); the concern for lack of charging facilities on long distance road trip, etc. These tastes affect the adoption of clean vehicles, and are not changed by pricing decisions.

I allow the taste for vehicle characteristics to be heterogeneous among consumers. Observed demographics, household income y_i and travel time to work t_i, affect how much consumers care about specific features. I would predict consumers with longer daily commute to care more about driving cost and HOV lane access. But the correlation between cost and income is ambiguous. I also allow the taste to vary by an unobserved random disturbance v_{im}.

The term ξ_{jm} in δ_{jm} represents unobserved preference for vehicle j that is common to all consumers within market m. For example, rural counties

The term ϵijm in μ_{ijm} represents unobserved preference of consumer i in market m towards vehicle j. I assume it has extreme value type I distribution.

2.4.1.2 Market shares

From utility function, I derive the probability that consumer i in market j will buy vehicle j:

$$s_{ijm} = \frac{\exp(\delta_{jm} + \mu_{ijm})}{1 + \sum_{k=1}^{J_m} \exp(\delta_{jm} + \mu_{ijm})}$$

and the market share of vehicle j in market m:

$$s_{jm} = \frac{1}{N_m} \sum_{i=1}^{N_m} s_{ijm}$$

where J_m is the total number of vehicles in market m, and N_m is the number of consumers, or market size of m. Equivalent of s_{ijm}, the probability of consumer i buys vehicle j conditional on i buys any vehicle is:

$$s_{ijm}^c = \frac{\exp(\delta_{jm} + \mu_{ijm})}{\sum_{k=1}^{J_m} \exp(\delta_{jm} + \mu_{ijm})}$$

Correspondingly, the market share of j conditional on vehicle purchasers, referred to as "conditional market share" in this paper, is:

$$s_{jm}^c = \frac{1}{N_m} \sum_{i=1}^{N_m} s_{ijm}^c$$

In the estimation I will use conditional market share on the demand side, since it is easier to match to the observed market share.

2.4.2 The supply side

2.4.2.1 Profit maximization

The supply side is actually a combination of dealership and manufacturers. The assumption is vertical integration: dealership are brand-specific, and all dealership are owned by the manufacturer of the brand. Hence, the objective of each manufacturer is to maximize the total profit from selling its products. Since demand is segregated between markets, manufacturer f who produces vehicle j in market m chooses the price of all its vehicles to maximize total profit from m:

$$\max_{p_m} \quad \Pi_{fm} = \sum_{j \in \mathscr{F}} (p_{jm} - mc_{jm}) s_{jm}$$

Optimal pricing p_{jm} is achieved from first order conditions with respect to p_{jm}:

$$s_{jm} + \sum_{k,j \in \mathscr{F}} \left[(p_{km} - mc_{km}) \frac{\partial s_{km}}{\partial p_{jm}} \right] = 0 \quad j = 1 \ldots J, \quad m = 1 \ldots M$$

To re-write in matrix term:

$$\begin{bmatrix} s_{11} \\ s_{21} \\ \vdots \\ s_{JM} \end{bmatrix} + \begin{pmatrix} B_{11} & & & \\ & B_{21} & & \\ & & \ddots & \\ & & & B_{FM} \end{pmatrix} \begin{bmatrix} b_{11} \\ b_{21} \\ \vdots \\ b_{JM} \end{bmatrix} = 0$$

where B_{fm} refers to the semi-elasticity matrix for manufacturer f in market m, with

$$B_{fm}(j,k) = \frac{\partial s_{km}}{\partial p_{jm}}, j, k \in \mathscr{F}$$

and s_{jm} and b_{jm} refer to the (unconditional) market share and markup of vehicle j in market m, respectively, i.e. $b_{jm} = p_{jm} - mc_{jm}$.

2.4.2.2 Marginal cost function

No direct information for marginal cost is available in the data. Hence, I assume that it takes the log-linear form:

$$\ln(mc_{jm}) = W_{jm}\gamma + \omega_{jm}$$

where W_{jm} denotes observable vehicle characteristics that affect marginal cost, and ω_{jm} denotes unobservable factors.

2.5 Estimation

I follow the tradition of BLP (1994) in estimating the random coefficient logit model from Section 4. I construct moments based on the assumption that the error term ξ is mean zero conditional on a set of instrument variables Z: $E[\xi|Z] = 0$. The variable brings endogeneity problem is transaction price, which may be correlated with the unobserved part ξ. In this section I first introduce the instruments used for price, and then describe the estimation details in Matlab.

2.5.1 Instruments

Endogeneity problem arises in the random coefficient logit model because the transaction prices are not randomly assigned, but determined by the supply side to maximize profit after observing consumer preferences. Although I have controlled several vehicle characteristics including driving cost, range, luxury brand and fuel type, it is likely that prices are still correlated to consumer preferences known by the supply side but unobserved to me. These unobserved preference for each vehicle is included in the term ξ in the model. As a result, ξ is not independent of price.

The instruments I use for transaction price follow the BLP tradition that are inspired by market competition. For each vehicle and each characteristics, I generate three measures to represent its "distance" to the market average, or "substitutability" in the market. The first set is the square difference between the vehicle characteristic and the average of all vehicles in the same county and quarter. The second set is the square difference between the vehicle characteristic and the average of all vehicles in the same county and quarter and belong to the same manufacturer. The third is the square difference between the vehicle characteristic and the average of all vehicles in the same county and quarter and have the same style. Similar instruments are used in Murry (2017).

There are two other possible ways to look for instruments. The first comes from the textbook definition. In the market equilibrium system that decide price and sales simultaneously, shocks from the supply side can be used as instruments since they are correlated to price but uncorrelated to consumer preference. For example, exogenous shocks to steel prices, dummy for manufactured in the U.S., etc. However, such variables are difficult to find in reality, and are often lack of variation across markets and between vehicles. Second, it is also suggested by Nevo (2000) that prices of the same product in other markets can be used as instruments, because they may both reflect vehicle-level variations in marginal cost. But in this paper the entire area of study is in California. There might be state-level campaign activities that affect consumer preferences in all markets simultaneously, and thus cause instruments to be correlated with the error term again.

Table 2.8 shows the "first-stage" results from regressing transaction prices on the instruments. It is not a direct byproduct of GMM, but helps to understand the validity of instruments. The dependent variable is transaction price, and the index 1, 2, 3 in all instrumental variables indicate which set they belong to. Column (1) uses all instruments generated, and column (2) excludes the one not significant. Most instruments have significant effects on prices, and the only exception is the squared difference of being PHEV and the market average. All the significant ones are used to construct moments.

2.5.2 Details and procedures

My estimation follows BLP (1994), minimizing a GMM objective function to get the parameter estimates in a random coefficient logit model for differentiated products. The data involved are described in Section 2, and the model is from Section 4.

Step 1. Draw 50 individuals for each county that vary in income and travel time to work according to the distribution in empirical data. Assume travel time to work is log-normal distributed, and income also has log-normal distribution within each household size group. First I assign household size to each individual according to the county-level empirical distribution. Next I generate income and travel time to work. For individual i in county j, its income y_{ij} and travel time t_{ij} are:

$$y_{ij} = \exp(ym + v_y ysd)$$

$$t_{ij} = tm + v_t tsd$$

where ym is log of median income, and ysd, standard deviation of $\log(y)$, is calculated from median and variance of income; tm and tsd are defined in the similar way for travel time. v_y and v_t are standard normal distributed.

In many other researches the individual valuation for vehicle characteristics is allowed to vary randomly. I do not include randomness in the heterogeneous part because (1) my goal is to explore how demand elasticity varies across income groups; and (2) adding more parameters into the heterogeneous part requires more instruments in the GMM estimation.

Distribution of household size, the mean and standard deviation of travel time to work, as well as the median and standard deviation of income by household size all come

Table 2.8: "First-stage": Price on Instruments

	(1)	(2)		(1)	(2)
VARIABLES	Price	Price	(continued)	Price	Price
IVCPHM1	501.9***	501.8***	IVRange3	-0.262***	-0.263***
	(20.25)	(20.26)		(0.0459)	(0.0459)
IVRange1	1.619***	1.625***	IVLuxury3	-11,320***	-11,304***
	(0.0851)	(0.0848)		(570.7)	(571.2)
IVLuxury1	-161,739***	-158,953***	IVHybrid3	35,198***	35,232***
	(32,982)	(32,683)		(2,768)	(2,769)
IVHybrid1	-266,646**	-255,651**	IVPHEV3	-38,783***	-37,560***
	(121,274)	(120,786)		(3,780)	(3,778)
IVPHEV1	123,391		IVBEV3	-69,616***	-69,574***
	(97,220)			(7,730)	(7,737)
IVBEV1	3.442e+06***	3.491e+06***	IVMPG3	17.41***	17.39***
	(540,182)	(541,578)		(1.29)	(1.292)
IVMPG1	-3.699**	-3.612**	Cost per 100 miles	2,592***	2,587***
	(1.59)	(1.589)		(43.2)	(43)
IVCPHM2	383.4***	384.2***	Range	62.06***	61.94***
	(24.42)	(24.38)		(6.041)	(6.035)
IVRange2	-1.798***	-1.804***	Luxury	31,440***	31,346***
	(0.0761)	(0.0758)		(1,002)	(991.9)
IVLuxury2	-22,961***	-22,978***	Hybrid	79,580	70,753
	(707.5)	(707.1)		(92,927)	(92,519)
IVHybrid2	135,713***	136,199***	PHEV	-204,658**	-98,060***
	(7,708)	(7,694)		(85,165)	(9,401)
IVPHEV2	169,967***	173,137***	BEV	-3.250e+06***	-3.297e+06***
	(9,934)	(9,680)		(496,578)	(497,797)
IVBEV2	256,991***	258,174***			
	(13,100)	(12,987)			
IVMPG2	-25.50***	-25.61***			
	(1.406)	(1.394)			
IVCPHM3	-575.1***	-574.8***	Observations	46,816	46,816
	(17.5)	(17.52)	R-squared	0.544	0.544

from ACS 2015 5-yr data on FactFinder. Note that the same individuals are used over time in each county.

Step 2. Let θ_1 and θ_2 denote the parameters in δ_j and μ_{ij}, respectively. With individual information, the theoretical conditional market share can be written as a function of δ and θ_2:

$$s_j^c(\delta, \theta_2) = \frac{1}{50} \sum_{i=1}^{50} \frac{\exp(\delta_j + \mu_{ij})}{\sum_{k=1}^{J} \exp(\delta_k + \mu_{ik})}$$

where $\mu_{ij} = \theta_2^{(1)} \frac{p_j - rij}{y_i} + \theta_2^{(2)} \ln t_i + \ln y_i X_j \theta_2^{(3)-(9)}$.

In other words, δ can be expressed as an inverse function of theoretical market shares and θ_2:

$$\delta_j = \delta_j(s^c, \theta_2)$$

By matching the theoretical market share s^c to the observed market share S^c, they can be further written into $\delta(\theta_2)$. Although it is impossible to write $\delta_j(\theta_2)$ into an explicit form, they can be numerically calculated by iteration until $s^c(\delta(\theta_2), \theta_2)$ and S^c converge, given any guess of θ_2. This contraction mapping method is used in BLP (1995) and later literature.

Step 3. The rest of the model is linear and thus can be estimated by OLS:

$$\begin{bmatrix} \delta(\theta_2) \\ \ln(mc) \end{bmatrix} = \begin{bmatrix} X & \\ & W \end{bmatrix} \begin{bmatrix} \theta_1 \\ \gamma \end{bmatrix} + \begin{bmatrix} \xi \\ \omega \end{bmatrix}$$

where $\delta(\theta_2)$ is the result from the last step, and the log of marginal cost, $\ln(mc)$, is calculated from observed transaction prices and markups. Markups are calculated from the FOC of the supply side, using theoretical purchase probability $s_{ij}(\delta(\theta_2), \theta_2)$. Note that in my model, the direct theoretical output is conditional market share s^c, and this unconditional market share is reweighted using the total market size in that county-quarter: $s = s^c \frac{totalsales}{numberofHH}$.

As a result, I get the OLS parameters and error term as functions of θ_2:

$$\begin{bmatrix} \theta_1(\theta_2) \\ \gamma(\theta_2) \end{bmatrix}, \begin{bmatrix} \xi(\theta_2) \\ \omega(\theta_2) \end{bmatrix}$$

Step 4. Error terms from the OLS regression are used to construct observed moments as GMM error terms. Instruments, Z, are all the instrumental variables described in this section, excluding those not significant in the "first-stage" regressions. Hence, I construct the observed GMM objective function:

$$G(\theta_2)^{obs} = [\xi(\theta_2)', \omega(\theta_2)'] \begin{bmatrix} Z & \\ & Z \end{bmatrix} W^{-1} \begin{bmatrix} Z & \\ & Z \end{bmatrix}' \begin{bmatrix} \xi(\theta_2) \\ \omega(\theta_2) \end{bmatrix}$$

where

$$W = \begin{bmatrix} Z & \\ & Z \end{bmatrix}' \begin{bmatrix} Z & \\ & Z \end{bmatrix}$$

Theoretically the GMM objective should equal to zero, if the underlying assumptions hold. I begin with an initial guess of θ_2, and search until $G(\theta_2)^{obs}$ is close to 0.

2.6 Results

In this section I discuss the results from structural estimation of the model. Table 2.9 reports the coefficients for demand. Table 2.10 shows the coefficients for supply.

2.6.1 Demand

Vehicle characteristics. The coefficient for total range is positive. The coefficients for driving cost is positive in the mean utility part, but is negative when combined with ln(income). Considering the randomly drawn households incomes are mostly larger than $\$25,000$, the actual coefficients for driving cost is negative for almost all households. And the larger households incomes are, the more sensitive they become with respect to driving cost. The coefficient for luxury brand is the opposite case: most households would prefer a luxury brand car, keeping other things equal, and the wealthier they are, the more they value luxury brand names. The income cutoffs for clean vehicles are much higher, with the coefficients in the mean utility part being -32, -28, and -29, respectively, and the heterogeneous coefficients being 22, 21, and 24. It implies that households with low income would prefer gasoline cars to clean vehicles, and the attitude is reversed when their incomes increase to a certain threshold. The threshold is unique for each fuel type: approximately $\$1,200,000$ for hybrids, $\$440,000$ for PHEVs, and $\$163,000$ for BEVs. The extremely high, almost out of sample, threshold for hybrids is quite surprising. A possible

Table 2.9: Estimation Results: Demand

	Parameter	Interaction with $\ln(y)/10$
Constant	14.77	18.61
	(3.41)	(4.07)
Cost per 100 miles/10	3.59	-4.49
	(1.02)	(1.15)
Range/100	0.39	0.40
	(0.01)	(0.08)
Luxury	-8.69	7.01
	(1.74)	(1.26)
Hybrid	-32.10	22.66
	(3.82)	(3.20)
PHEV	-28.39	21.03
	(3.70)	(1.82)
BEV	-29.44	24.77
	(2.14)	(2.26)
(p-rebate)/y	-3.34	
	(0.05)	
ln(travel time)	2.18	
	(0.06)	

explanation is that most of the privileges of hybrids are captured by the coefficient of total range. The left unquantifiable part of hybrids is actually not as popular as gasoline cars.

Price. The price of a car enters the utility function in the form of its ratio to household income. The coefficient is -3.34, intuitively indicating that financial burden associated with buying the vehicle brings dis-utility. In the sense of scale, it means increase the price by $\$5,000$ for a household earning $\$50,000$ annually would be approximately equivalent to decrease the original vehicle's total range by 42 miles, keep other things equal. However, offering $\$4,000$ by CVRP would not be enough to switch such a consumer from gasoline cars to an equivalent BEV in other respects. This coefficient also determines the shape of demand elasticities directly, which will be discussed next.

Travel time. The coefficient for travel time to work is a positive 2.18, probably because the vehicle values higher for those who use it more intensively. Transformed to willingness-to-pay, a consumer who travels 60 minutes daily and earns $\$50,000$ annually would be willing to pay an impressive $\$22,517$ more than a 30 minutes traveler of the same pay. The economically significant number suggests that travel time is an important concern in vehicle purchase decisions, and thus it might be useful to explore which vehicle characteristics long distance commuters value the most. In the current model, I do not interact travel time with vehicle characteristics. But it can be done in the same way as income when more instruments are used in the simulated moments.

The role of heterogeneity. Heterogeneity comes from two dimensions: consumers and vehicles, and they are often highly correlated. In the model, the term of price ratio and travel time represents pure consumer heterogeneity, while the interactions between income and vehicle characteristics represents consumers tendency of self-selection into buying different vehicles. For all the vehicle characteristics, the coefficients of the heterogeneous part are economically significant compared to those in the mean utility part, which indicates the importance of designing income-tiered policies.

2.6.2 Price elasticities

The main goal of the structural part is to study demand elasticities of different income groups on vehicles of various fuel type. The functional form of how price enters the utility function actually puts an underlying assumption on how elasticities vary by income. In this part, I first explain the feature of elasticities that comes from the model, and then show the results from estimated coefficients.

Own- and cross-price elasticities. For vehicle j, own-price elasticity is:

$$e_j = \frac{\partial s_j/s_j}{\partial p_j/p_j} = \frac{1}{N}\frac{\alpha p_j}{s_j}\sum_{i=1}^{N}\frac{s_{ij} - s_{ij}^2}{y_i}$$

For vehicle j and q, cross-price elasticity is:

$$e_{jq} = \frac{\partial s_j/s_j}{\partial p_q/p_q} = -\frac{1}{N}\frac{\alpha p_q}{s_j}\sum_{i=1}^{N}\frac{s_{ij}s_{iq}}{y_i}$$

Note that I assume here p_j is not changing with p_q, which may not be true in the market equilibrium if j and q belong to the same supplier. Hence, this cross-price elasticity only applies to comparative statics analysis, and is not an equilibrium result.

For the purpose of heterogeneity study, I further define the corresponding elasticities of household i:

$$e_j^i = \frac{\alpha p_j}{s_j}\frac{s_{ij} - s_{ij}^2}{y_i}$$

and

$$e_{jq}^i = -\frac{\alpha p_q}{s_j}\frac{s_{ij}s_{iq}}{y_i}$$

Note that $\alpha < 0$ and $s_{ij} \in (0, 1)$, hence own-price elasticity is negative, while cross-price elasticity is positive. Individual-level elasticity is proportional to the inverse of income y_i. Keep other things constant, individual own-price elasticity e_j^i is the largest in absolute value when individual probability of buying s_{ij} reaches 50%, and smallest when the individual almost certainly buys or not buy. Since $s_{ij} < 50\%$ in almost all the cases, it is safe to say that the absolute value of e_j^i increases with s_{ij}. The case of cross-price elasticity is more complicated, with e_{jq}^i proportional to both s_{ij} and s_{iq}, and s_{ij} and s_{iq} are correlated.

Comparative statics study: heterogeneity by income and vehicle. In this part I explain the marginal effect of consumer and vehicle characteristics on calculated elasticity. The purpose is to understand estimated price elasticities between income groups and across vehicles.

1. The effect of income on elasticities

$$\frac{\partial |e_j^i|}{\partial y_i} = \frac{\alpha p_j}{s_j} \frac{s_{ij} - s_{ij}^2}{y_i^2} < 0$$

and

$$\frac{\partial |e_j^i|}{\partial y_i} = \frac{\alpha p_q}{s_j} \frac{s_{ij} s_{iq}}{y_i^2} < 0$$

Hence, for changes in either the price of vehicle j or the price of other vehicles, the higher household income is, the less sensitive the household is in making decisions of whether to purchase j.

2. The effect of price on elasticities

For simplicity and purpose of illustration, assume that household i is the representative consumer of the market, i.e. $s_{ij} = s_j$.

$$\frac{\partial |e_j^i|}{\partial p_j} = \frac{|\alpha|}{y_i} \left(1 - s_j - p_j \frac{\partial s_j}{\partial p_j}\right)$$

$$\frac{\partial |e_{jq}^i|}{\partial p_j} = \frac{-\alpha p_q}{y_i} \frac{s_q}{p_j}$$

Since $\frac{\partial s_j}{\partial p_j} < 0$ and $\frac{\partial s_q}{\partial p_j} > 0$,

$$\frac{\partial |e_j^i|}{\partial p_j} > 0$$

$$\frac{\partial |e_{jq}^i|}{\partial p_j} > 0$$

Therefore, more expensive vehicles have market shares that are more sensitive to price changes, both of itself and of other vehicles.

2.6.3 Supply

Vehicle characteristics. In marginal cost functions, I use the same set of X_j as in demand estimation, except that driving cost is replaced by MPG. The coefficient of MPG is negative, probably because the most high-end vehicles usually have low MPG.

Table 2.10: Estimation Results: Supply

	Parameter
Constant	10.05
	(1.93)
MPG/10	-0.59
	(0.23)
Range/100	0.21
	(0.08)
Luxury	1.02
	(0.34)
Hybrid	0.86
	(0.37)
PHEV	2.31
	(1.54)
BEV	6.01
	(1.85)

The coefficients of range and luxury brand are both positive, indicating that the marginal cost is higher to build cars with longer range and cars of luxury brands. Especially, the coefficients of clean vehicles are all positive and large, with that of hybrids being 0.86, PHEVs being 2.3, and BEVs being around 6. Imagine a gasoline vehicle with marginal cost of $\$30,000$ and MPG of 30. If its BEV version is developed with 200 miles range when fully charged and MPGe of 100, without changing any of the other characteristics (gasoline cars usually have range of 350 miles), it is estimated that its marginal cost will be increased to $\$132,449$. The high marginal cost of clean vehicles, especially PHEVs and BEVs, partly explains why manufacturers and dealers are not willing to sell them at lower prices. The high marginal cost here includes both R&D investment and cost of building material, for example, battery and electric engine. Without supply-side data, I cannot distinguish between the two sources.

2.7 Counter-factual Simulations

An application of the model is to simulate counter-factual policy consequences of clean vehicle rebates. The same reasoning that a model is needed applies here: because exogenous financial incentives affect both demand and price through the simultaneous equation system, both sides of the system need to be re-estimated to land on the new market equilibrium price and sales.

In this section I briefly describe the process of finding market equilibrium under new rebate designs, and then discuss counter-factual policies to study. Results are still in process and is not included in this version.

2.7.1 Iteration under counter-factual rebates

The main challenge to do counter-factual analysis is to solve for prices and market shares simultaneously under the new market equilibrium. I employ an iteration process for the purpose that is similar in solving for $\delta(\theta_2)$.

Step 1. For household i buying vehicle j, the new rebate is r^n_{ij}. Calculate the probability of i buying j using new rebate and original transaction price $p_j^{(0)}$:

$$s_{ij}^{c,(0)} = \frac{\exp(\delta_j + \mu_{ij}^{(0)})}{\sum_{k=1}^{J} \exp(\delta_k + \mu_{ik}^{(0)})}$$

where $\mu_{ij}^{(0)} = \alpha \frac{p_j^{(0)} - r^n_{ij}}{y_i} + X_j \tilde{\beta}_i$.

thus, the corresponding market share is:

$$s_j^{c,(0)} = \frac{1}{50} \sum_{i=1}^{5} 0 s_{ij}^{c,(0)}$$

Step 2. Plug it into the FOC of the supply side, and calculate the optimal prices $p_j^{(1)}$:

$$s_j^{(0)} + \sum_{k,j \in \mathscr{F}} \left[(p_k^{(1)} - mc_k) \frac{\partial s_k^{(0)}}{\partial p_j^{(0)}} \right] = 0$$

where mc_j are marginal costs estimated in the main analysis. This leads to a set of new optimal prices $p^{(1)}$.

Step 3. There will be a gap between $p^{(0)}$ and $p^{(1)}$. Re-calculate market shares using $p^{(1)}$, and iterate until $p^{(n+1)}$ and $p^{(n)}$ converge. The ultimate $p^{(n)}$ and $s^{(n)}$ will be taken as the new market equilibrium.

2.7.2 Policies for study

I propose two possible rebate designs for study. First, assume CVRP further reduces its income cap to 700% Federal Poverty Line and increases the low income subsidy to $\$5,000$ for PHEVs and $\$6,000$ to BEVs. This design is a closer mimic of the experimental EFMP Plus-up program implemented in San Joaquin Valley and South Coast of California. The EFMP Plus-up was initiated as a trial to provide progressive clean vehicle subsidies, and resulted in the current income tiered design of CVRP, only that EFMP Plus-up still has much stricter restrictions on participants. Its income cap is 400% FPL and requires participants to retire an old, polluting vehicle. On the other hand, consistent with its focus on the bottom income group, it accepts clean vehicle purchases of both new and used, hybrids together with plug-ins. However, a few reduced form studies, including my self's, found its effect on used clean vehicle sales to be insignificant. Hence, I do not adopt these features of EFMP Plus-up, and only simulates the one-step further version of CVRP with more restrictive income eligibility.

Second, assume the federal tax credit sets an income cap at $\$500,000$ for households. The current federal tax credit offers $\$7,500$ to BEVs and around $\$3,000-5,000$ to PHEVs, depending on its fuel economy. BEV and PHEV buyers receive the deduction based on their tax payments. The policy has the major defect of being regressive: the rich receives the entire credits, while the poor whose total tax payment is lower than the credits, gets only the payment back. Keeping its tax credits format and combining with income cap, I simulate the impact of a less regressive policy on the clean vehicle market.

2.8 Conclusion

In this paper I provide evidence that clean vehicle incentives affect both the market shares and transaction prices, and that households respond to financial incentives in heterogeneous ways, depending on their income level and vehicle fuel type. I estimate a static market equilibrium model of the new automobile market using data from California vehicle registrations and online reported transaction prices, and calculate demand elasticities by consumer income and vehicle fuel type. Without considering heterogeneous elasticities and equilibrium transaction prices, the effect of counter-factual subsidies might be overestimated. For identification, I use a set of instruments inspired by the competitive market structure to construct GMM objective function.

Clean vehicle subsidies are important for the industry, not only because it incorporates the environmental externality into consumer decision, but also because it incentivizes manufacturers to invest in R&D through spillover effect. These subsidy programs are offered in a generous amount in the U.S., on federal, state and local level alike. Most of them support PHEV and BEV purchases and are tiered by vehicle fuel type, not income. Hence, it is important to understand their impact on sales and prices, and realize their shortcomings in incentivizing and benefiting the less wealthy. I run simulations for two counter-factual policies, both aiming at benefiting the low income group while keeping the impact on clean vehicle sales. The first sets stricter income cap and offers higher in a California state-level cash rebate program. The second combines the federal tax credit with an income cap to correct for its regressiveness.

This paper is an application of the BLP model that has been widely used in demand estimation for a market of differentiated products. It also sets an example of comparing relatively novel products with traditional ones that are partly comparable. For example, in this case, driving cost, luxury brand, transaction price, range, etc. are the observable, quantifiable characteristics that clean vehicles and gasoline cars share. But indicators for hybrids, PHEVs and BEVs still play an important role in demand elasticity after controlling for those variables. And the importance varies by consumer income. Understanding how subsidies work for heterogeneous consumers and for different products is the key to understanding the effectiveness of policies.

CHAPTER 3

The Heterogeneous Impacts of Credit Expansion on the Housing Market

3.1 Introduction

Does a financial market expansion provide the same benefits to households of all income levels? The question is important in evaluating whether policies designed to expand or tighten the market increase or reduce financial inequality. In this chapter, we answer the first question by looking at one specific shock to the credit market: the national financial deregulation starting 1994.

We find that the credit shock only affects households who buy low value properties. We also investigate the mechanism behind the results, and find that it is mainly driven by changes in the down payments among low value properties buyers, or equivalently, their access to the credit market.

The policy shock we study is the passing of Riegle-Neal Act in 1994, which allows banks to enter states they are not head-quartered in. The outcomes are twofold in our context. First, banks were able to provide better services to customers through extended networks of branches. And second, the competition on the credit supply side intensified in local markets. Both may lead to higher levels of credit supply. A strand of literature has evaluated the impact of this policy (Rice and Strahan, 2010; Favara and Imbs, 2015; etc.). In this paper, we focus on the heterogeneous consequences on house buyers with different wealth levels.

Our first analysis examines whether the housing market responds to the deregulation, and whether the response differentiates by property value. The results indicate that only lower-valued properties are significantly affected by the deregulation. The effect also depends on local housing supply elasticity. Between counties with the same level of deregulation, capital gains at all quantiles increase more in the county with inelastic supply, at least in scale.

Our second analysis investigates the role of credit market in transmitting the impact to the housing market using instrumental variable regression. We begin by showing that multiple measures of bank credit supply, including loan issuance, volume of loans and loan-to-income ratio, are elevated after the deregulation. Furthermore, these credit supply shocks cause the capital gains of lower-valued properties to increase, while median and higher-valued properties are not affected significantly.

We recognize four channels of the impact: through down payment, through credit score requirement, through loan-to-income ratio, and through borrowing cost. Taking Los Angeles as an example, we show that the down payment among lower-valued property buyers plunged after the deregulation, while the down payment among other buyers remained stable. It provides evidence that the credit expansion may have stimulated the demand of lower-valued properties by allowing households with limited savings to enter the credit market.

Our results are also important because they represent a formal test of the model developed in the insightful paper by Landvoigt et al (2015). In their paper, they provide evidence that households with low-valued houses have larger capital gains during booms. We find that their model is consistent with the exogenous variation generated by the 1994 Riegle-Neal Act.

3.2 Deregulation: The 1994 Riegle-Neal Act

We use the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 as an exogenous source of the credit market expansion, which allowed state law makers to legitimate out-of-state banks stepping inside the borders.

The Act was signed by President Clinton on September 29, 1994. By that time, many states already had state-level rules allowing out-of-state banks to acquire in-state banks under certain circumstances, but a national framework was absent. IBBEA was a result of the general trend. It provided uniform standards for banks to serve their customers wherever they are, and to better meet credit needs.

IBBEA allowed banks to acquire other banks in any state after September 29, 1995; and allowed banks in different states to merge into one branch network after June 1, 1997. As a concession to the opposition from small banks and insurance companies, states are also allowed to choose whether to opt-out by June 1, 1997. While all states allowed interstate banking (except for Texas and Montana), their openness differs in four aspects: (1) allowance of de novo interstate branching; (2) allowance of interstate branching by acquisition of single branch or portions of an institution; (3) the minimum age of the institution for acquisition; and (4) statewide deposit cap. Rice and Strahan (2010) provided index for interstate branching restrictions from 1994 to 2005: the index is set to zero for states most open to out-of-state banks entry, and add one for each of the barriers added.

Table 3.1 presents the timeline and index of deregulation for states in our sample. Some states may appear multiple times, indicating later changes in legislation. The deregulation index is an integer ranging from 0 to 4. It is computed by subtracting the restriction index of Rice and Strahan (2010) from 4, the total number of barriers.

The Act is arguably an exogenous shock to the credit market. People may suspect that it was a result of the increasing demand for credit. While it is true that the Act was passed in purpose for the banks to better serve their customers, no sudden increase in demand was expected around that time. In fact, the efforts started from as early as the 1980s to remove the restrictions on interstate banking but had failed, partly due to the opposition from small financial institutions. By 1990, 46 states had already allowed interstate banking acquisition in certain circumstances. It was in 1993 that the federal government decided to unify the state level regulations with a new law. Hence, it is reasonable to believe that the pass of the Act was not correlated with the growth in credit needs.

The results from Favara and Imbs (2015) also suggest that the deregulation affected the credit market exogenously, by comparing the loan issuance behavior of out-of-state banks and institutions not covered by the deregulation.

Table 3.1: Banking Deregulation Index by State in 1994-2000

State	**Deregulation index**	**Implementation date**	**In sample?**	**State**	**Deregulation index**	**Implementation date**	**In sample?**
Alabama	2	5/31/1997	y	Nebraska	0	5/31/1997	y
Alaska	3	1/1/1994		Nevada	1	9/29/1995	y
Arizona	1	9/1/1996	y	New Hampshire	0	6/1/1997	y
Arkansas	0	6/1/1997		New Jersey	3	4/17/1996	y
California	1	9/28/1995	y	New Mexico	1	6/1/1996	y
Colorado	0	6/1/1997	y	New York	2	6/1/1997	y
Connecticut	3	6/27/1995	y	North Carolina	4	7/1/1995	y
Delaware	1	9/29/1995		North Dakota	1	5/31/1997	
DC	4	6/13/1996		North Dakota	3	8/1/2003	
Florida	1	6/1/1997	y	Ohio	4	5/21/1997	y
Georgia	1	6/1/1997	y	Oklahoma	0	5/31/1997	y
Hawaii	1	6/1/1997	y	Oregon	1	7/1/1997	y
Idaho	1	9/29/1995		Pennsylvania	4	7/6/1995	y
Illinois	1	6/1/1997	y	Rhode Island	4	6/20/1995	y
Indiana	4	6/1/1997		South Carolina	1	7/1/1996	y
Indiana	3	7/1/1998		South Dakota	1	3/9/1996	
Iowa	0	4/4/1996		Tennessee	1	6/1/1997	y
Kansas	0	9/29/1995		Tennessee	2	5/1/1998	y
Kentucky	0	6/1/1997		Texas	0	8/28/1995	y
Kentucky	1	3/17/2000		Texas	2	9/1/1999	y
Kentucky	1	3/22/2004		Utah	2	6/1/1995	
Louisiana	1	6/1/1997		Utah	3	4/30/2001	
Maine	4	1/1/1997		Vermont	2	5/30/1996	
Maryland	4	9/29/1995	y	Vermont	4	1/1/2001	
Massachusetts	3	8/2/1996	y	Virginia	4	9/29/1995	y
Michigan	4	11/29/1995	y	Washington	1	6/6/1996	y
Minnesota	1	6/1/1997	y	West Virginia	3	5/31/1997	
Mississippi	0	6/1/1997		Wisconsin	1	5/1/1996	y
Missouri	0	9/29/1995		Wyoming	1	5/31/1997	
Montana	0	9/29/1995					
Montana	0	10/1/2001					

Source: Rice and Strahan (2010).

3.3 Data

3.3.1 Housing price quartiles

We compute quartiles of house prices dating back to 1994 using the mortgage loan information provided by DataQuick. DataQuick reports the transaction type of each loan. We exclude transactions involved in distress events or within arm's length. Transactions are also dropped if they have zero or missing transaction values, or have loan-to-value ratios greater than one.

From the raw data, we construct an unbalanced panel dataset on county and year level.[1] For each county and year, we compute the price distribution of properties sold that year in the county, including the lower quartile, median, the upper quartile and average. To avoid data quality issues, we drop the observation if there are fewer than 100 valid transactions reported. The period of study is from 1994 to 2000. By the end of 2000, most states, especially states with active economic activities, have completed the legislation process of deregulation.

Table 3.2 reports the summary statistics for housing prices by year. The number of in-sample counties varies by year and ranges from 130 to 290, because of the unbalanced nature of our data. The sample size increases over time in general, and represents approximately 5-10% of all counties in the United States. All prices are normalized to 2009 dollars.

3.3.2 Credit supply

We use the online data set provided by Favara and Imbs (2015) for credit market information. They constructed the data set from the Home Mortgage Disclosure Act (HMDA) database. HMDA consists of loan applications from two types of institutions: depository institutions and independent mortgage companies (IMCs). Depository institutions can be further categorized into commercial banks, thrifts and credit unions (TCUs). Note that the Riegel-Neal Act applied to commercial banks only.

[1] DataQuick does not have full geographical coverage until later years, but it is not correlated with the local economic conditions. Rather, it is because the company started in California and gradually expanded over years.

Table 3.2: Summary Statistics of Housing Price Quartiles (in thousand dollars)

	Full sample (1994-2000)				
	Mean	Std.dev	Min	Max	Observations
Q1	104.152	61.557	3.075	451.095	1,533
Median	151.811	75.155	13.368	613.49	1,533
Q3	216.693	102.754	39.29	854.074	1,533
Average	176.149	86.256	31.746	687.645	1,533
	1995				
	Mean	Std.dev	Min	Max	Observations
Q1	99.695	59.599	5.239	301.875	140
Median	144.349	72.436	19.645	415.815	140
Q3	202.592	96.924	39.29	586.725	140
Average	164.825	81.408	35.54	469.573	140
	2000				
	Mean	Std.dev	Min	Max	Observations
Q1	113.606	71.305	16.239	451.095	280
Median	166.523	88.775	33.682	613.49	280
Q3	241.29	123.226	73.378	854.074	280
Average	196.523	102.274	53.549	687.645	280

Source: DataQuick.

Favara and Imbs (2015) extracted credit market measures by county, year, and lender type, including the number of mortgages originated, the volume of mortgages, loan-to-income ratio, number of branches (from Summary of Deposits FDIC), etc. The loan-to-income ratio is computed by dividing the total loan amount from HMDA by the total income from IRS.

Table 3.3 summarizes the log difference of three credit market measures in our sample: loans originated by banks, volume of loans by banks, and the loan-to-income ratio by banks. Both out-of-state and in-state banks are included.

Table 3.3: Credit Market Measures from Commercial Banks

	Full sample (1994-2000)				
	Mean	Std.dev	Min	Max	Observations
	Log difference				
Number of loans originated	0.136	0.405	-4.382	5.517	1,520
Volume of loans	0.172	0.427	-5.744	5.008	1,520
Loan-to-income ratio	0.106	0.427	-5.819	4.928	1,520
	1995				
	Mean	Std.dev	Min	Max	Observations
	Log difference				
Number of loans originated	0.207	0.694	-0.693	4.86	135
Volume of loans	0.273	0.764	-0.365	4.117	135
Loan-to-income ratio	0.212	0.764	-0.402	4.139	135
	2000				
	Mean	Std.dev	Min	Max	Observations
	Log difference				
Number of loans originated	0.035	0.14	-0.411	0.838	279
Volume of loans	0.053	0.134	-0.286	0.893	279
Loan-to-income ratio	-0.019	0.134	-0.316	0.831	279

Source: Favara and Imbs (2015); HMDA.

3.4 The Descriptive Correlation between Property Value and Deregulation

This section describes the correlation between the housing market and the deregulation.

3.4.1 Strategy

In this analysis, we predict that property value increased faster in response to the deregulation event, especially properties with low base values. We estimate:

$$\ln p_{it}^q - \ln p_{i,t-1}^q = \beta_0^q + \beta_1^q \text{Deregulation}_{i,t-1} + \beta_2^q X_{it} + \eta_i + \gamma_t + \epsilon_{it} \quad (3.1)$$

Where p_{it}^q refers to the q-th quartile of housing prices in county i and year t. Thus, the dependent variable indicates the growth rate of the q-th price quartile from year (t-1) to year t. The main explanatory variable, $\text{Deregulation}_{i,t-1}$, indicates the deregulation index in county i by the end of year (t-1). Note that we allow the effect of deregulation,

β_1^q, to differentiate between price quartiles.

X_{it} varies by county and time. It consists of the log difference of three variables, income, population, and the Herfindahl index of mortgage market concentration computed by Favara and Imbs (2015). The purpose is to control for factors other than the deregulation that may affect housing price.

X_{it} also includes the lagged log difference of the three variables, as well as the lagged dependent variable, to control for possible momentum in the growth of housing price. Besides, we control for the interaction of deregulation and housing supply elasticity. The elasticity is estimated by Saiz (2010). Hence, we allow the marginal effect of deregulation on property value to be correlated with the supply elasticity. Intuitively, if a county has very elastic housing supply (e.g. due to geographical conditions), then it is easier for the housing stock to respond to market price fluctuations, and thus the impact should be smaller of any exogenous shocks on the equilibrium housing price.

County fixed effects η_i are controlled so that time-invariant factors, such as other policies regarding the housing market or geographical characteristics, do not affect the results. Similarly, year fixed effects γ_t are controlled to exclude trends in property values that are universal among counties.

ϵ_{it} is the error term corresponding to county i and year t. We allow it to cluster within state, considering the deregulation index varies at state level. Besides, states with higher number of counties are also likely to have larger standard errors, because of geographical variations, etc. Hence, each observation is weighted by the inverse of counties within the state.

3.4.2 Results

Table 3.4 presents the results for the reduced-form regression. Panel A allows for the interaction between the impact of deregulation and housing supply elasticity. As expected, the growth rates of housing prices are positively related to the deregulation index, and negatively correlated with the interaction of the index and supply elasticity, at all quartiles. They are also negatively correlated with their own lagged growth rate. It indicates that, first, the return to housing market is likely to increase at all quartiles amid deregula-

Table 3.4: The Effects of Deregulation on the Housing Market

	Dependent: County-level housing price			
	(1)	(2)	(3)	(4)
	Q1	Median	Q3	Average
	Panel A			
Lagged deregulation index	0.0451**	0.0316***	0.0237***	0.0241***
	(0.0204)	(0.00957)	(0.00793)	(0.00779)
Lagged deregulation * elasticity	-0.0147**	-0.0145***	-0.0123**	-0.0120**
	(0.00716)	(0.0042)	(0.00497)	(0.00466)
Lagged dependent variable	-0.295***	-0.187***	-0.223***	-0.212***
	(0.0358)	(0.0581)	(0.0428)	(0.0468)
X_{it}	y	y	y	y
County FE	y	y	y	y
Year FE	y	y	y	y
Observations	819	819	819	819
R-squared	0.188	0.157	0.253	0.253
Number of county	238	238	238	238
	Panel B			
Lagged deregulation index	0.0138*	0.00453	0.00114	0.00232
	(0.00761)	(0.0037)	(0.00304)	(0.00277)
X_{it}	y	y	y	y
County FE	y	y	y	y
Year FE	y	y	y	y
Observations	1,212	1,212	1,212	1,212
R-squared	0.088	0.137	0.243	0.237
Number of county	298	298	298	298

tion. Second, among counties with the same level of deregulation, property value increases faster where the housing supply is less elastic. And third, the return of property value follows a mean reversion pattern.

The impact of deregulation is not homogeneous to all properties. Consider a county with housing supply elasticity of 1.6.[2] The point estimate for the marginal effect of deregulation is 0.02158 for the lower quartile, 0.0084 for the median price, and 0.00402 for the upper quartile. In other words, for each regulation relaxed, the return of property value will increase by 2.2%, 0.8%, and 0.4% at the lower quartile, median, and upper quartile, respectively. The impact decreases with property value. It is not surprising to see housing supply elasticity affect the responsiveness of housing price, in light of the past literature.

Panel B of Table 3.4 reports the reduced-form results if we ignore the heterogeneity in housing supply elasticity. Here the marginal effect of deregulation is represented by the parameter of the policy indicator alone. It is still positive but only significant for the lower quartile of property value, suggesting that the lower quartile is affected the most by the deregulation in both scale and statistical significance. Note that this marginal effect may be less accurate than Panel A in predicting a single county, because it is not allowed to vary with elasticity.

3.5 The Effect of Credit Expansion on the Housing Market

Is the impact of deregulation on capital gains achieved through the credit market? And does the credit market explain the heterogeneity across property values? In this part we answer the two questions using an instrumental regression approach. We first examine whether the deregulation affects measures of the credit market, and then estimate the impact of credit shocks on the housing market.

[2] 1.6 is the median housing supply elasticity in our sample of the year 1995.

3.5.1 Strategy

3.5.1.1 The impact of deregulation on the credit market

Regarding the effects on financial market measures, we estimate:

$$\ln L_{it} - \ln L_{i,t-1} = \alpha_0 + \alpha_1 \text{Deregulation}_{i,t-1} + \alpha_2 X_{it} + \eta_i + \gamma_t + \nu_{it} \tag{3.2}$$

Where L_{it} refers to the measures of credit supply by commercial banks of county i in year t. Three measures are used: the number of loans originated, the total volume of loans originated, and the loan-to-income ratio. Like in equation (3.1), we control for the log difference of population, income and mortgage market concentration, as well as county fixed effects and time fixed effects.

Credit suppliers can be categorized into three groups in our context: in-state banks, out-of-state banks, and other institutions including thrifts and credit unions (TCUs) and independent mortgage companies (IMCs). An in-state bank in state A also serves as an out-of-state bank in state B. Therefore, we do not distinguish out-of-state and in-state loans. Without doubt, TCUs and IMCs may also adjust their behavior in market equilibrium. This indirect effect of deregulation is not taken into account in this study.

3.5.1.2 House prices and credit supply, using the deregulation as an instrument

Using equation (3.2) as first stage, we further estimate:

$$\ln p^q_{it} - \ln p^q_{i,t-1} = \theta^q_0 + \theta^q_1 (\ln L_{it} \widehat{- \ln} L_{i,t-1}) + \theta^q_2 X_{it} + \eta_i + \gamma_t + \upsilon_{it} \tag{3.3}$$

Where $(\ln L_{it} \widehat{- \ln} L_{i,t-1})$ is the instrumented log difference of credit supply. We allow the marginal effect of credit market to vary with housing supply elasticity by including the interaction of the credit measure and elasticity in X_{it}. We expect to find θ^q_1 positively significant for the lower quartile as in the reduced-form, which means the lower-valued property will experience higher capital gains in capital expansion.

3.5.2 Results

3.5.2.1 First stage: the effect of deregulation on the credit market

Table 3.5 presents the effects of deregulation on the credit market. All three measures of credit supply from commercial banks, loans originated, the volume of loans, and loan-to-income ratio, increased significantly in response to the deregulation. For each regulation relaxed, the growth rate of loans originated will increase by 4.08%, that of the loan volume will increase by 4.15%, and that of loan-to-income ratio will increase by 3.96%.

Table 3.5: The Effects of Deregulation on Commercial Bank Loan Issuance

	(1)	(2)	(3)
	Number of loans	Volume of loans	Loan-to-income ratio
Lagged deregulation index	0.0408***	0.0415**	0.0396**
	(0.0147)	(0.0158)	(0.0155)
X_{it}	y	y	y
County FE	y	y	y
Year FE	y	y	y
Observations	1,397	1,397	1,397
R-squared	0.147	0.151	0.147
Number of county	308	308	308

Deregulation allowed out-of-state banks to enter the credit market through opening new branches or acquisition. Hence, banks were able to extend their network of branches, hedge default risk, and achieve economy of scale by participating in the national market. As a result, banks became more capable in providing credit to customers, both in and out of the home state. In contrast, the capability of TCUs and IMCs to provide credit to customers should not be affected directly by the deregulation event.

3.5.2.2 Second stage: the effect of credit supply on property value

Table 3.6 reports the results for the instrumental regression. The three panels represent different endogenous variables: loans originated in Panel A, volume of loans in Panel

B, and loan-to-income ratio in Panel C. The results indicate that the effects of credit market on property values are heterogeneous across value brackets. More specifically, credit market expansion significantly increases the return of property value at the lower quartile, but the effects on the median and upper quartile are not statistically significant. Besides, scales of the effect are quite consistent between the three credit supply measures. When the credit supply measure increases by 1%, the return to property value of the lower quartile will increase by approximately 0.51-0.52%. The effects of credit expansion on median and upper quartile are smaller in scale than on the lower quartile, as in Table 3.4, though insignificant.

As suggested by Table 3.4, the return of housing price has a mean reversion pattern. Hence, we control for the lagged dependent variables in the second stage. Also, counties with more elastic housing supply are affected less by the deregulation. Therefore, we control for the interaction of credit supply and housing supply elasticity to allow non-linear effects of credit expansion. The insignificant estimates indicate that the marginal effect of credit expansion on property value is uncorrelated with housing supply elasticity.

3.6 Mechanism on the Impacts of Credit Expansion

How did the deregulation affect housing price through credit market? And why does the impact decrease with property value? In this section we analyze several possible mechanisms behind the results.

Credit expansion are implemented mainly in four ways: (1) relaxation of down payment requirement; (2) relaxation of minimum credit score required; (3) increase in loan-to-income allowed; and (4) drop in borrowing costs. (1) and (2) lower the entry barrier to apply for credit, while (3) and (4) raise the upper bound of loan amount a home buyer could ask for. Combined together, they lead to increases in the number of loans originated, the total volume of loans and the loan-to-income ratio, as shown in the first stage.

Moreover, the implementation affects mainly low-income households, or low-valued property buyers, instead of median or high-income households, except for the fall of borrowing cost which may benefit everyone. For home buyers with good socio-economic

Table 3.6: The Effects of Credit Market Expansion on the Housing Market: Instrumented by the Deregulation

	Dependent: County-level housing price			
	(1)	(2)	(3)	(4)
	Q1	Median	Q3	Average
	Panel A			
Instrumented number of loans	0.512*	0.154	0.0313	0.0444
	(0.259)	(0.131)	(0.11)	(0.0894)
Lagged dependent variable	-0.292***	-0.181***	-0.210***	-0.200***
	(0.0378)	(0.0553)	(0.0368)	(0.0433)
Instrumented number of loans * elasticity	0.0181	0.0449	0.0522	0.0586
	(0.0915)	(0.0555)	(0.0484)	(0.0558)
R-squared	0.184	0.147	0.242	0.244
	Panel B			
Instrumented volume of loans	0.528*	0.169	0.047	0.0622
	(0.263)	(0.129)	(0.103)	(0.0862)
Lagged dependent variable	-0.292***	-0.181***	-0.212***	-0.201***
	(0.0376)	(0.0557)	(0.0367)	(0.0435)
Instrumented volume of loans * elasticity	0.000669	0.0318	0.0402	0.045
	(0.0821)	(0.0478)	(0.0454)	(0.0519)
R-squared	0.184	0.147	0.241	0.243
	Panel C			
Instrumented loan-to-income ratio	0.527*	0.158	0.0327	0.051
	(0.272)	(0.135)	(0.111)	(0.0924)
Lagged dependent variable	-0.292***	-0.181***	-0.211***	-0.201***
	(0.0377)	(0.0554)	(0.0367)	(0.0435)
Instrumented loan-to-income * elasticity	0.019	0.0467	0.0539	0.0572
	(0.0918)	(0.056)	(0.0502)	(0.0575)
R-squared	0.184	0.148	0.243	0.244
Observations	819	819	819	819
Number of county	238	238	238	238

status, their credit scores and household incomes are usually high enough not to be bound by the constraints. Hence, the relaxation of credit score requirement and loan-to-income ratio are mostly relevant to low-income loan applicants.

Table 3.7: Down Payment in Los Angeles by Housing Price Quartile (Median)

	House price quartiles			
	1	2	3	4
1990	25%	20%	25%	32%
1991	20%	20%	21%	30%
1992	20%	11%	20%	30%
1993	20%	10%	20%	25%
1994	20%	10%	20%	25%
1995	9%	5%	10%	20%
1996	5%	5%	14%	20%
1997	5%	5%	20%	20%
1998	5%	5%	20%	20%
1999	5%	5%	20%	25%
2000	5%	5%	20%	23%

Source: DataQuick.

Evidence shows that the same applies to down payment: buyers of lower-valued properties paid less after the deregulation, while the upfront payment ratio of other buyers remained approximately 20%. Take Los Angeles as an example. Table 3.7 shows its median down payment by house price quartiles. The down payment is calculated from the total loan amount and transaction value from DataQuick. After the deregulation was implemented in California in 1995, the median down payment of all quartiles plummeted, though the highest-valued group fell the least: the first quartile from 20% to 9%, the second quartile from 10% to 5%, the third quartile from 20% to 10%, and the highest quartile from 25% to 20%. The fall in the third and fourth quartile turned out to be temporary and bounced back in two and four years, respectively. The median down payment of the lowest quartile fell further to 5% in the following year.

It reveals the divergent pattern of entry barrier to the credit market between lower-valued and higher-valued property buyers. In the credit expansion, it is significantly easier for lower-valued property buyers to enter the market, while the threshold for other buyers remains relatively stable. Possibly the down payment requirement is only binding for lower-valued property buyers.

In sum, the credit market may help increase the housing demand in multiple ways due to the deregulation. Noticeably, it is the lower-income home buyers that were mostly affected through these channels. For example, households with limited savings may be unable to pay for the upfront amount before the banking credit expansion, but are able to pay after that. It helps explain why only the capital gains of lower-valued properties are lifted by the credit expansion.

3.7 Conclusions

An identical policy can have heterogeneous effects on different people. As a result, it may increase or reduce financial inequality if the impact differentiates on the rich and the poor. Hence, it is important to examine whether the policy consequences are heterogeneous, and to understand its mechanism, in evaluating such policies.

In this paper, we study the impact of a national banking deregulation on housing prices at each quartile. As expected, the deregulation stimulated credit supply of banks by removing the obstacles for them to operate across states. Using the deregulation as an exogenous credit shock, we find that there is an increase of 0.51-0.52% in the capital gains of lower-valued properties in response to a 1% increase in credit supply. In contrast, the capital gains of median and higher-valued properties remained almost constant.

The heterogeneity is rooted in the implementation of credit expansion. Thanks to extended networks of branches and intensified competition, households who were unable to meet the down payment requirements may now be granted access to the credit market with lower upfront amount requirement. This leads to increased housing demand and equilibrium prices. The additional demand usually represents low-income buyers who only participate in the sub-market of lower-valued properties. In comparison, wealthier buyers usually pay a default 20% of the transaction value as down payment, both before and after the deregulation.

Does it mean the credit expansion reduces financial inequality? We would be cautious about making that conclusion. On one hand, marginal home buyers undoubtedly benefit from the additional access to the credit market, and lower-valued home owners are better-off from the increased capital gain. On the other hand, however, families preparing to buy lower-valued houses anyway can be hurt by the price upswing.

Our approach can also be applied to the recession period to examine whether low-valued houses suffer large capital losses, as symmetrical to the boom period. Using a variation that is not exogenous, we find that the losses are similar for all property values in most markets. Hence, a test to the model in recession using exogenous shock is left to be done.

Appendix

A Appendix to *Information Spillover Effects When Clean Vehicle Rebates Are Rationed: Evidence from California's Low-Income Rebate Program*

A1 Pre-treatment trend of clean vehicle sales

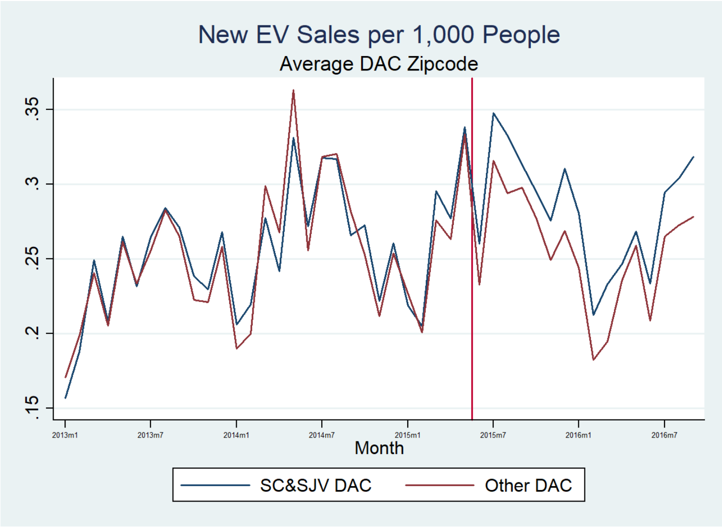

Figure A1: Pre-treatment trend of clean vehicle sales

A2 Treatment Effects by Region: Shorter Period

Table A1: Treatment Effects of EFMP and Plus-up By Region: January 2014 to March 2016

	Y: Clean Vehicle Sales			Y: Density of Clean Vehicle Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Types	Hybrid	PEV	All Types	Hybrid	PEV
South Coast						
Treated*After	1.014***	0.824***	0.190***	0.0388***	0.0294***	0.00939***
	(0.118)	(0.097)	(0.0641)	(0.00478)	(0.0038)	(0.00274)
R-squared	0.205	0.188	0.077	0.127	0.12	0.044
Observations	14,472	14,472	14,472	14,472	14,472	14,472
Number of zip	536	536	536	536	536	536
San Joaquin Valley						
Treated*After	0.097	0.0437	0.0533	0.0107**	0.0105**	0.000172
	(0.101)	(0.0816)	(0.0578)	(0.00512)	(0.00412)	(0.00291)
R-squared	0.125	0.127	0.039	0.075	0.078	0.021
Observations	10,503	10,503	10,503	10,503	10,503	10,503
Number of zip	389	389	389	389	389	389

A3 The calculation of damages in dollar per gasoline and electricity mile

A3.1 Method

This section describes how damages per mile are calculated. In many ways we adopt the methods and estimates from Holland et al., (2016).

Emission per gasoline mile

We consider the marginal damage per mile of nitrogen dioxide (NOx), sulfur dioxide (SO_2), carbon dioxide (CO_2), particulate matter less than 0.025mm (PM 2.5) and volatile organic compounds (VOCs) on the road. Holland et al., (2016) used the combined GREET model[3] and Tier 2 emission standards for the purpose, but we replace the federal Tier 2 with CA standards.[4] Estimates from both sources are vehicle-specific, based on MPG and vehicle category.

[3] https://www.arb.ca.gov/fuels/lcfs/ca-greet/ca-greet.htm.

[4] https://www.dieselnet.com/standards/us/ld_ca.php.

- SO_2 and CO_2: emission is assumed to be proportional to the inverse of MPG. The baseline estimate is 0.00616 g/mile of SO_2 at 23.4 MPG according to the GREET model, and 8,920 metric ton/gal for CO_2.

- NOx: we refer to the emission rate in CA emission standards[5] for each vehicle bin.

- PM2.5: we add up the CA emission standards for on-road pollution with the GREET estimates from tires and brakes.

- VOCs: we add up the CA emission standards[6] for on-road pollution with the GREET estimates from evaporation.

The next step, damages per emission unit for each county, is estimated and reported in Holland et al., (2016).

Damages (\$) per electricity mile

We consider the emission from generating electricity at each power plant per hour within the California power grid. We assume all electricity demands are met within the Western Grid, but not necessarily in the same county where the demand emerges. We directly adopt the damage per kWh by county and hour estimated by Holland et al., (2016), and weight electricity demand from clean vehicles using the Electric Power Research Institute (EPRI) charging profile.[7] The damage per kWh is estimated by regressing plant and hour specific emission on county electricity consumption, and multiplying the estimated marginal emissions by damage per emission unit.

[5] The CA category of each model is found here: `https://www.arb.ca.gov/msprog/onroad/cert/cert.php`. The information for 1992 Chevrolet S10, 1992 Acura Integra and 1993 Ford Ranger cannot be found. For now we assume them to be "Tier 1", the least clean type of passenger cars.

[6] We used NMOG in CA standards due to the lack of VOCs standards, which is defined more broadly.

[7] EPRI estimates the charging load profile of plug-in electric vehicles by hour. The profile reflects the intuition that charging demand is high during working hours and overnight.

A3.2 Shares of Top Retired and Replacement Models

Table A2: Shares of Top Retired and Replacement Models Among Subsidized Consumers

		Vehicle	Income		
			$\leq 225\% FPL$	226-300% FPL	301-400% FPL
Retired		Honda Accord	10.58%	9.37%	4.17%
		Toyota Camry	6.88%	10.93%	4.17%
		Toyota Corolla	5.21%	6.25%	12.50%
		Honda Civic	6.95%	4.69%	16.67%
		Nissan Sentra	1.28%	3.13%	0.00%
		Nissan Altima	1.21%	1.56%	0.00%
		Nissan Maxima	1.13%	1.56%	4.17%
		Ford Explorer	0.98%	3.13%	4.17%
		Chevrolet S10	0.91%	0.00%	0.00%
		Acura Integra	0.76%	3.13%	0.00%
		Ford Ranger	0.76%	1.56%	0.00%
Replacement	Hybrid	Toyota Prius	14.21%	26.56%	
		Kia Optima Hybrid	7.41%	6.25%	
		Honda Civic Hybrid	4.99%	3.13%	
		Toyota Camry Hybrid	4.01%	4.69%	
		Hyundai Sonata Hybrid	3.10%	3.13%	
	PHEV	Chevrolet Volt	14.51%	15.63%	29.17%
		Toyota Prius Plug-in	3.33%	3.13%	20.83%
		Ford Fusion Energi	2.80%	1.56%	12.50%
		Ford C-Max Energi	2.49%	3.13%	8.33%
	BEV	Nissan Leaf	12.09%	15.63%	12.50%
		Ford Focus Electric	1.59%	1.56%	4.17%

A3.3 In-sample Fuel Efficiency of Retired and Replacement Vehicles

Table A3: Fuel Efficiency of Representative Retired and Replacement Vehicles Among Subsidized Consumers

		Vehicle	MPG Gas and Hybrid Cars	kWh per mile PHEVs and BEVs
Retired		1995 Honda Accord	18.62	
		1995 Toyota Camry	17.81	
		1996 Toyota Corolla	20.45	
		1996 Honda Civic	25.36	
		1992 Nissan Sentra	22.00	
		1999 Nissan Altima	19.39	
		1996 Nissan Maxima	17.18	
		1997 Ford Explorer	13.22	
		1992 Chevrolet S10	17.28	
		1992 Acura Integra	18.86	
		1993 Ford Ranger	17.46	
Replacement	Hybrid	2013 Toyota Prius	48.51	
		2013 Kia Optima Hybrid	35.90	
		2012 Honda Civic Hybrid	43.23	
		2013 Toyota Camry Hybrid	38.81	
		2013 Hyundai Sonata Hybrid	35.90	
	PHEV	2012 Chevrolet Volt		0.37
		2013 Toyota Prius Plug-in		0.30
		2014 Ford Fusion Energi		0.38
		2013 Ford C-Max Energi		0.38
	BEV	2012 Nissan Leaf		0.35
		2012 Ford Focus Electric		0.33

Notes: (1) The year of each model is calculated as the average release year of that model in the Plus-up application database. (2) We assume fuel efficiency depreciates at 1% annually since its release year.

A3.4 Spillover Fuel Efficiency of Retired and Replacement Vehicles

B Appendix to *Green Dollars: The Impact of Clean Vehicle Subsidies*

B1 From direct to indirect utility function

The indirect utility function I use in Section 4 is taken from traditional IO literature, with slight difference in the definition of X. It can be interpreted as the equivalent of a direct utility function. Assume that household i maximizes its utility by choosing vehicle j and travel miles m. The associated utility is:

$$u_{ij} = X_j\beta_i + \alpha\frac{p_j + d_j m_i - r_{ij}}{y_i} + \eta_i \ln m_i + \epsilon_{ij}$$

where p_j is the price of vehicle j, d_j is the cost per mile of driving, m_i is the household choice of miles to travel, and r_{ij} is rebate. The second term in the utility represent the ratio of total cost of owning j to the household income, or the financial burden related to vehicle j, and the third term quantifies the joy of driving the vehicle. Given each j, the household chooses m_i such that:

$$\alpha\frac{d_j}{y_i} + \frac{\eta_i}{m_i^*} = 0$$

$$m^* = \frac{y_i\eta_i}{-\alpha d_j}$$

Plug into u_{ij} to get the indirect utility function:

$$\begin{aligned} u_{ij}^* &= X_j\beta_i + \alpha\frac{p_j - \frac{y_i\eta_i}{\alpha} - r_{ij}}{y_i} + \eta_i \ln\frac{y_i}{-\alpha d_j} + \epsilon_{ij} \\ &= X_j\beta_i + \alpha\frac{p_j - r_{ij}}{y_i} - \eta_i + \eta_i(\ln y_i - \ln\alpha - \ln d_j) + \epsilon_{ij} \end{aligned}$$

The indirect utility function solves the problem of unobserved optimal miles to travel. The term $\eta_i(\ln y_i - \ln d_j - \ln\alpha - 1)$ goes into the heterogeneous part of market share function in the same way as $X_j\beta_i$.

Table A4: Fuel Efficiency of Representative Retired and Replacement Vehicles Among Spillover Sales

	Replacement Vehicle	MPG Gas and Hybrid Cars	kWh per mile PHEVs and BEVs	Retired Vehicle	MPG Gas and Hybrid Cars	kWh per mile PHEVs and BEVs
Hybrid	Toyota Prius	52		Toyota Corolla	31	
	Lexus CT200h	42		Lexus GS200t	26	
	Kia Optima	37		Kia Optima	28	
	Lexus ES	40		Lexus ES	24	
	Toyota Camry	39		Toyota Camry	28	
	Ford Fusion	41		Ford Fusion	25	
	Hyundai Sonata	40		Hyundai Sonata	24	
	Toyota RAV4 Hybrid	32		Toyota RAV4	25	
	Lexus RX	30		Lexus RX	23	
	Lincoln MKZ	40		Lincoln MKZ	25	
PHEV	Chevrolet Volt	42	0.31	Chevrolet Cruze	34	
	Ford Fusion	38	0.37	Ford Fusion	41	
	BMW i3	39	0.29	Lexus CT200h	42	
	Ford C-MAX	38	0.37	Ford C-Max	39	
	BMW X5	24	0.59	BMW X5	25	
	Toyota Prious Plug-in	50	0.29	Toyota Prius	52	
	Porsche Cayenne	22	0.69	Porsche Cayenne	21	
	Volvo XC90	25	0.58	Volvo XC90	24	
	Porsche Panamera	25	0.51	Porsche Cayenne	21	
	BMW 330	31	0.47	BMW 330	27	
BEV	Tesla Model S		0.34	BMW 740i	24	
	Fiat 500		0.30	Fiat 500	34	
	Nissan Leaf		0.30	Toyota Prius	52	
	Tesla Model X		0.36	Porsche Cayenne	21	
	Volkswagen Golf		0.29	Volkswagen Jetta	44	
	Chevrolet Spark		0.28	Chevrolet Spark	34	
	BMW i3		0.27	Lexus CT200h	42	
	Mercedes-Benz B-Class		0.40	Mercedes-Benz C350e	30	0.56
	Kia Soul EV		0.32	Hyundai Ioniq	55	
	Ford Focus		0.32	Ford Focus	34	

B2 Derive price elasticities

The market share function for vehicle j is:

$$s_j = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp(\delta_j+\mu_{ij})}{\sum_{k=1}^{J}\exp(\delta_k+\mu_{ik})}$$

where

$$\delta_j = X_j\bar{\beta}+\xi_j$$

$$\mu_{ij} = \alpha\frac{p_j-r_{ij}}{y_i}+\lambda\ln(t_i)+\ln(y_i)X_j\tilde{\beta}$$

Own-price elasticities. For vehicle j:

$$\begin{aligned}
\frac{\partial s_j}{\partial p_j} &= \frac{1}{N}\sum_{i=1}^{N}\frac{\partial s_{ij}}{\partial p_j}\\
&= \frac{1}{N}\sum_{i=1}^{N}\frac{\left[\sum_{k=1}^{J}\exp(\delta_k+\mu_{ik})\right](\exp(\delta_j+\mu_{ij}))\frac{\alpha}{y_i}-(\exp(\delta_j+\mu_{ij}))^2\frac{\alpha}{y_i}}{\left[\sum_{k=1}^{J}\exp(\delta_k+\mu_{ik})\right]^2}\\
&= \frac{1}{N}\sum_{i=1}^{N}\frac{\alpha}{y_i}(s_{ij}-s_{ij}^2)
\end{aligned}$$

Hence, the elasticity is:

$$e_j = \frac{\partial s_j/s_j}{\partial p_j/p_j} = \frac{1}{N}\frac{\alpha p_j}{s_j}\sum_{i=1}^{N}\frac{s_{ij}-s_{ij}^2}{y_i}$$

Cross-price elasticities. For vehicle j and q, ignoring the endogeneity between vehicle prices from the same manufacturer for now:

$$\begin{aligned}
\frac{\partial s_j}{\partial p_q} &= \frac{1}{N}\sum_{i=1}^{N}\frac{-(\exp(\delta_j+\mu_{ij}))(\exp(\delta_q+\mu_{iq}))\frac{\alpha}{y_i}}{\left[\sum_{k=1}^{J}\exp(\delta_k+\mu_{ik})\right]^2}\\
&= -\frac{1}{N}\sum_{i=1}^{N}\frac{\alpha}{y_i}s_{ij}s_{iq}
\end{aligned}$$

Hence, the elasticity is:

$$e_{jq} = \frac{\partial s_j/s_j}{\partial p_q/p_q} = -\frac{1}{N}\frac{\alpha p_q}{s_j}\sum_{i=1}^{N}\frac{s_{ij}s_{iq}}{y_i}$$

The effect of price on elasticities. For vehicle j:

$$\begin{aligned}
\frac{\partial|e_j^i|}{\partial p_j} &= \frac{|\alpha|}{y_i}\frac{p_j(s_{ij}-s_{ij}^2)}{s_j}\\
&= \frac{|\alpha|}{y_i}\frac{s_j\left[s_{ij}-s_{ij}^2+p_j\left(\frac{\partial s_{ij}}{\partial p_j}-2s_{ij}\frac{\partial s_{ij}}{\partial p_j}\right)\right]-p_j(s_{ij}-s_{ij}^2)\frac{\partial s_j}{\partial p_j}}{s_j^2}
\end{aligned}$$

To simplify, assume that the market is filled with representative consumer i, i.e. $s_{ij} = s_j$. Thus,

$$\begin{aligned}
\frac{\partial |e^i_j|}{\partial p_j} &= \frac{|\alpha|}{y_i} \frac{s_j \left[s_j - s_j^2 + p_j \left(\frac{\partial s_j}{\partial p_j} - 2 s_j \frac{\partial s_j}{\partial p_j} \right) \right] - p_j (s_j - s_j^2) \frac{\partial s_j}{\partial p_j}}{s_j^2} \\
&= \frac{|\alpha|}{y_i} \frac{s_j (s_j - s_j^2) + s_j p_j \frac{\partial s_j}{\partial p_j} (1 - 2 s_j - 1 + s_j)}{s_j^2} \\
&= \frac{|\alpha|}{y_i} \left(1 - s_j - p_j \frac{\partial s_j}{\partial p_j} \right)
\end{aligned}$$

Under the same simplifying assumption,

$$\begin{aligned}
\frac{\partial |e^i_{jq}|}{\partial p_j} &= \frac{-\alpha p_q}{y_i} \frac{s_j \left(s_{ij} \frac{\partial s_{iq}}{\partial p_j} + \frac{\partial s_{ij}}{\partial p_j} s_{iq} \right) - s_{ij} s_{iq} \frac{\partial s_j}{\partial p_j}}{s_j^2} \\
&= \frac{-\alpha p_q}{y_i} \frac{s_j \left(s_j \frac{\partial s_q}{\partial p_j} + \frac{\partial s_j}{\partial p_j} s_q \right) - s_j s_q \frac{\partial s_j}{\partial p_j}}{s_j^2} \\
&= \frac{-\alpha p_q}{y_i} \frac{s_q}{p_j}
\end{aligned}$$

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