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Essays in Transportation and Environmental Economics

DISSERTATION

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for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

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DEDICATION

To
my father Prasanta Chakraborty
for his love and faith in me.

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ABSTRACT OF THE DISSERTATION

Essays in Transportation and Environmental Economics

By

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This thesis uses the tools of applied econometrics to study the impact of economic incentives on household welfare and decision-making and the environmental outcome of urban transportation policies in the U.S. and in developing countries.

Transportation is an essential component of day-to-day life. An extensive transportation system offers mobility, expanding individuals' access to employment opportunities, agglomeration benefits to firms and employees, reduced trade costs, and an overall increase in productivity. The positive effects of an efficient transportation network in an economy are often accompanied by rising motorization rates. This, in turn, can lead to air pollution, road congestion, and increasing dependence on fossil fuels. In the past few decades, climate change concerns have made policymakers and governments agencies in both developed and developing countries incentivize improvement in fuel economy of vehicles as well as promote alternative fuel vehicles.

Alternative fuel vehicles currently arriving in the market offer better driving performance compared to their predecessors, and their market penetration is higher than before. However, most people still do not consider these alternative fuel vehicles as a substitute of traditional gasoline cars. Incentives offered to consumers to promote adoption have achieved varied results. The first chapter of the dissertation studies the stated vehicle transaction decisions

of 3,154 survey respondents located in the state of California. While the effectiveness of policy incentives like tax credits and rebates is found to be more universal, the effect of High Occupancy Vehicle (HOV) lane permit or free parking benefit on adoption decision depends on the likelihood of the household being able to use the benefits. In addition, familiarity with an alternative fuel technology is found to be positively correlated with the preference for electric battery or hydrogen fuel cell vehicles. Prior ownership of a hybrid vehicle made the household more likely to purchase an alternative fuel vehicle in the future. This persistence in choice behavior can be attributed to heterogeneity among vehicle purchasers or considered as a sign of positive experience. Experience can reduce skepticism about alternative fuel vehicles and induce future adoption. Accounting for the number of years of ownership of alternative fuel vehicles, the results show that more experience has a positive effect on the probability of repurchase of the same or a newer technology vehicle. This result contributes towards a long standing debate of whether the incentives work only as a marketing mechanism or does it have any long term benefits. The positive correlation in preference pattern and the willingness to pay measures indicate that even if the price-based incentives work as a marketing mechanism they play an important role in initiating potential state dependence in purchase behavior to improve adoption in the long run.

In recent years, emerging economies like India and China have been experiencing the externalities related to increased motorization. Urbanization accompanied with increasing per capita income has led to a rise in private automobile demand. Historically, the infrastructure of major metropolitans in these emerging economies was not designed to support a sudden rise in the use of automobiles. As a result, a majority of these metropolitans suffer from congestion and pollution from greenhouse gas (GHG) emissions. The local government and policymakers in these economies are considering a variety of policies like to scrap old polluting vehicles, impose fuel standards, cordon tolls, and driving restrictions to address these issues. Driving restrictions has been implemented in several metropolitan cities in emerging economies like Beijing, China, Santiago, Chile, Mexico City, Mexico, São Paulo, Brazil, Bogotá, Colombia, and recently New Delhi, India. According to this policy, cars with license plate numbers ending with certain digits are allowed to be driven on separate days of the week. A number of studies have shown that though the license plate based policy is effective in the short run in reducing local pollutants as well as GHG emissions, it is not effective in the medium or long run. In spite of these results, it is considered more equitable compared to price-based policies like congestion tax or a cordon toll that may impose a greater financial burden on the low-income commuters. At present, there is a limited number of studies that consider the distributional effect of the policy. The second chapter on license-plate-based driving restriction policy considers the distributional effect of the policy in comparison to a cordon toll and a vehicle mile tax by analyzing the mode choice of commuters in Santiago, Chile. Analysis of different policy scenarios suggests that though the restriction has a negative distributional effect on all commuters, in the absence of a revenue recycle mechanism the effect is less adverse in comparison to a vehicle mile tax or a cordon toll for the same level of reduction in total car trips.

Transportation and the power sector are the leading sources of GHG emissions in the U.S. Policies and programs trying to reduce GHG emissions from the power sector like the federal Clean Power Plan, rebates and tax credits for the adoption of rooftop photovoltaic cells, and the renewable portfolio standard incentivizes investment in renewable energy resources. The programs have increased the share of renewable resources in the grid but, utilities are finding it hard to integrate these intermittent sources of energy into the regular dispatch module. In the transportation sector, the policy focus has mostly been on encouraging adoption of electric vehicles (EV). The latter has zero tailpipe emissions but has to be connected to the grid to operate the vehicle. Electricity pricing will play a major role in dealing with this quandary. The third chapter on electricity pricing and EV charging behavior considers the environmental impact of shifting from tiered or block pricing structure to a time-of-use rate structure that matches consumption with the time-varying cost of electricity production. The results provide evidence supporting the decision to change the pricing structure as marginal emissions of carbon dioxide is lower under the time-of-use rate structure compared to the tiered pricing plan. Moreover, the analysis of emissions in each time-of-use period brings forth the importance of defining the periods such that utilities and environmentalists can maximize the benefits of EV adoption and the increasing share of renewable energy resources in the power sector.

Chapter 1

Adoption of Alternative Fuel Vehicles: A Stated Preference Analysis of Personal Vehicle Transaction Choice

1.1 Introduction

Alternate fuel vehicles currently arriving in the market have better performance metrics compared to their predecessors in the 1990s, and their market penetration is higher than before. However, most people still do not consider these alternate fuel vehicles as a real alternative to traditional gasoline cars.

In 2012, the California Air Resource Board (CARB), with its Advanced Clean Car Program, set the target that by 2025 the emissions of new automobiles should contain 34 percent fewer global warming gases and 75 percent lower smog-forming emissions. CARB aims to put at least 1.5 million zero emission or near-zero emission vehicles on the road by 2025. To achieve the goal, the state of California has spent till date $409,081,565 (US dollars) in a rebate program called the Clean Vehicle Rebate project. The main goal of the incentive programs- tax rebates, subsidies, subsidized charging stations, or high occupancy vehicle (HOV) lane access, is to reduce the cost of adoption across income groups and create peer effects. However, these programs are expensive and therefore, policymakers designing them need to carefully assess the benefits.

To promote adoption of low or zero emission vehicles, government agencies need to first understand how consumer demand is affected by the various incentives offered with the alternate fuel vehicles- whether consumers respond to purchase incentives and if they value the different types of incentives similarly. Secondly, it is important to identify the long term effects of theses incentives- whether experience with a new technology vehicle affect future purchase decisions.

In this paper, using stated preference (SP) data a vehicle choice model is estimated to analyze the factors that affect the purchase decision of a vehicle buyer. Two main results emerge from the study. First, familiarity with a new fuel technology is positively related to future preference for alternate fuel vehicles. The persistence in choice behavior can be attributed to inertia among vehicle purchasers or positive experience. Experience can reduce skepticism about alternate fuel vehicles and induce future adoption. Accounting for the number of years of ownership of alternate fuel vehicles, the results show that current ownership has a positive effect on the probability of repurchase of the same or newer technology. Second, the stated vehicle purchase intentions of 3,154 survey respondents indicate that, while the effect of policy incentives like tax credits and rebates that reduce the purchase price of the vehicles are more universal, the effect of HOV lane permit or the free parking benefit depends on the likelihood of the household being able to use the benefit.

While price is a major factor in the purchase decision, vehicle attributes like body type, range, acceleration rate, maintenance costs, and refueling cost (both time and money) also matter [Daziano, 2013], [Achtnicht et al., 2012], [Ozaki and Sevastyanova, 2011], [He et al., 2012]. Using results from the vehicle choice model, I estimate the willingness to pay for alternate fuel vehicles in different body types. The estimates indicate that consumers who may switch from gasoline cars are likely to choose one that offers them comparable attributes and serves a similar purpose as the vehicle they are substituting.

Conditional logit model is used to estimate the vehicle choice model in the paper. The data used for analysis is drawn from a California-wide stated preference survey of potential car buyers administered by the California Department of Transportation along with the California Energy Commission (CEC). The survey was conducted between 2010 and 2012. SP data is typically required to study the demand for a product that is new or is currently not available in the market, which is often the case with alternate fuel vehicles [Jenn et al., 2013]. Even though a fair number of alternative fuel vehicles are currently available in the market, the variety of models and vehicle types are still limited. Stated preference approach makes it possible to study the choice behavior of households considering a wider range of vehicle options combined with different fuel types than available in the market. Both categories and the level of the different features affecting choice can be varied for the hypothetical vehicle options. In other words, when compared to the information revealed by any automobile sales dataset, the SP set-up allows identification of a wide range of features that may play a vital role in purchase decisions now and in the future.

Additionally, vehicle purchase decision can be driven by motivational constructs like environmental concerns [Ozaki and Sevastyanova, 2011], [Heffner et al., 2007], and [He et al., 2012]. Except for motivational constructs, the SP data of potential vehicle purchasers used in the paper allow exploration of all the factors in the purchase decision of a household in tandem.

1.2 Literature Review

There is an extensive literature studying the adoption of new technology vehicles from different perspectives: policy effects, drivers of technology adoption, heterogeneity in adopters, and the effect of technology experience. One of the earliest studies related to the demand for alternate fuel vehicles was done by [SRI, 1978]. The SRI study concentrated only on electric vehicle adoption and their potential market share. In recent years, there has been considerable research using both SP and revealed preference (RP) data on adoption of electric vehicles and other alternate fuel vehicles like the hydrogen fuel cell vehicles, plug-in hybrids, and their environmental benefits [Axsen et al., 2009], [Axsen et al., 2009], [Jensen et al., 2013], [Hackbarth and Madlener, 2013], [Zivin et al., 2014], [Lieven, 2015].

Government agencies try to promote the adoption of alternative fuel vehicles both by providing subsidized support infrastructure [Handbook, 2012] as well as giving direct financial incentives for alternate fuel vehicle purchase [Diamond, 2009]. Looking at the effect of tax credits and subsidies on the sales of the Toyota Prius, Sallee [2011] found that there was a higher demand during the high tax credit and rebate period following the Energy Policy Act in 2005. Gallagher and Muehlegger [2011] considered the relative efficacy of state sales tax waivers, income tax credits and non-tax incentives on adoption of hybrids and found that the type of tax incentive offered is as important as the value of the tax incentive. The paper also analyzed the extent to which consumer adoption of hybrid-electric vehicles (HEV) in the United States from 2000-2006 could be attributed to government incentives, changing gasoline prices, or consumer preferences for environmental quality or energy security, and found that they are associated with 6, 27 and 36 percent of hybrid sales from 2000-2006, respectively.

In addition to price-based incentives, the Government also offers usage-based incentives like the HOV lane access and parking benefits to adopters. Using household location information, Tal and Nicholas [2014] explored the effect of the HOV lane benefit on hybrid vehicle sales. They found that proximity to an HOV lane as well as the consumer's travel pattern impacts the likelihood to purchase the currently available new technology vehicles. Gallagher and Muehlegger [2011] considered the impact of HOV lane access on purchase of hybrid vehicles between 2000-2006 and found that, except in Virginia, the effect of the usage-based incentive was insignificant. The general consensus in the literature is that purchase incentives positively affect adoption by reducing the adoption cost of new technology vehicles, but the usage-based incentives have more targeted beneficiaries.

Lastly, while the short term effects of incentives and adoption of alternative fuel vehicles have been extensively discussed in the economics literature, there are limited number of studies looking at the effect of experience with new technology vehicles on purchase decisions. The marketing literature has multiple evidences of state dependence or past purchase of a product affecting future purchase behavior due to loyalty, learning, or both [Keane, 1997], not many studies have explored the effect of learning and experience on adoption of new technology vehicles. Analyzing choice data from a two-wave SP experiment in which information about respondents' attitude for an EV was collected before and after they experienced the vehicle for three months, Jensen et al. [2013] concluded that individual preferences change significantly after a real experience with an EV, particularly in terms of driving range, top speed, fuel cost, and battery life. In an earlier study, considering the difference in adoption rates between states with higher share of first generation Toyota Prius and Honda Insight owners, [Heutel and Muehlegger, 2015] concluded that better experience with the Prius encouraged a higher adoption rate of hybrid technology vehicles in the first set of states. In this paper, using information on vehicle holding of households and their stated preference, the effect of past purchase decision on future vehicle choice is analyzed. However unlike [Jensen et al., 2013], in the current setup, learning effects cannot be differentiated from the possibility of inertia in purchase decision.

1.3 Survey Data

The SP data for the vehicle choice model is obtained from the 2010-2012 California Vehicle Survey (CVS) of potential car buyers administered by the California Energy Commission (CEC)[1]. The vehicle survey is conducted periodically to update the California Personal Vehicle Choice (PVC) model. The PVC model projects the number and type of vehicles owned, along with annual vehicle miles traveled (VMT) and fuel consumption by personal cars and light-duty trucks, in California. Households are selected for the survey by a random selection process from all residential addresses in the study area. The sample, including households from 58 counties of California and various demographic and socio-economic groups (age, gender, education, income etc.) was chosen to represent as closely as possible the population residing in the state.

The pool of respondents for the CVS was a subset of the households surveyed in the 2010-2012 California Household Travel Survey (CHTS) conducted by the California Department of Transportation covering 42,431 households and 109,113 individuals. The CHTS collects information on household structure, vehicle inventory, vehicle usage characteristics, demographic data, basic employment, and commuting habits of the household/respondent along with the household's intended vehicle transaction.

The CVS had two rounds. Total 4,140 households out of 7,031 participants completed the first round of the CVS. The first round required households to complete a questionnaire requesting detailed information on demographics like income, its vehicle holding and usage, including data on vehicle model, fuel type, vehicle leasing habits, and purchase intentions in the coming 5 years in terms of vehicle model, fuel type, and price. It was designed primarily to garner insights into consumer preferences for vehicles and their attributes. Out of the 4,140 households, 709 did not qualify for the second round of the survey. Therefore, a

[1] The data was made available through a feasibility study used to build a new vehicle choice and utilization model.[TN 71379 06-26-13 CEC Power Point Presentation - 03 Light Duty Vehicle Survey.pdf]

total of 3,431 households completed the second round of the survey, containing eight stated preference discrete-choice experiments. All of these 3,431 households had expressed intention to purchase or lease at least one vehicle in the next five years during the first part of the survey. It is assumed that the stated choices are consistent, and the households' SP vehicle choice would be similar to their revealed preference in the first round of the survey.

In the survey, each choice set described four hypothetical vehicles from which households were asked to choose their preferred vehicle. The 4 hypothetical options were characterized by 14 attributes: fuel type, body type, number of models available, model year, vehicle price, purchase incentives, MPG/fuel economy, cost per 100 miles, fuel availability (given by time taken to get to the refueling station), time to refuel, vehicle range, trunk space, maintenance cost, and acceleration rate (time to reach 60 mph). A brief description of the attributes describing the vehicle options in the choice experiment is provided in Table A.1 in Appendix A.1. Attributes of the hypothetical options like body type, price and refueling preferences were customized to be similar (but not identical) to the household's description of their next intended vehicle purchase, as expressed in the first part of the survey. An example of the stated preference task/choice experiment from the survey is given in Figure 1.1 and the descriptive statistics of the choice variables are given in Table 1.1.

Table 1.1: Descriptive statistics of Choice Attributes

Variable	Mean	Std. Dev.	Min	Max
Acceleration Rate/Time to reach 60 mph(mins)	8.89	2.56	3.1	15.3
Cost per 100 miles (US $)	13.35	6.14	3.6	47.5
Time to Refuel (@ station/home/work in mins)	174.48	427.64	1	3,120
Cost of Maintenance (US $)	450.87	113.38	219	829
Miles per Gallon	34.37	18.74	7.6	112.6
Vehicle Price (US $)	33,414.75	22,188.08	177	571,792
Vehicle Range (miles)	411.80	180.44	80	1,000
Time to Refuel Station (mins)	6.25	4.89	0	15
Trunk Space (cubic feet)	47.71	52.40	1	271

[1] Total number of observation is 100,928

Respondents were asked to assume that the hypothetical vehicle options only differed with

Figure 1.1: Stated Preference Survey: Sample Vehicle Choice Set

Choice Set 3

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

Vehicle Choice 1	Vehicle A	Vehicle B	Vehicle C	Vehicle D
Vehicle Type	Van	Van	Minivan	Standard Pick-up Truck
Fuel Type	Gasoline only vehicle	Diesel Hybrid Electric Vehicle (HEV)	Gasoline Plug-in Hybrid Electric Vehicle (PHEV)	Compressed Natural Gas (CNG) only vehicle
Vehicle Models Available	6	3	3	1
Model Year	New (2013)	New (2013)	New (2013)	New (2013)
Vehicle Price	$32,550	$47,165	$38,073	$45,264
Purchase Incentive	None	None	None	None
MPG/Fuel Economy	18.2	27.5	38.1	17.7
Cost per 100 Miles	$26.89	$12.39	$13.36	$9.15
Refueling Station (Time it takes to get to this type of station)	Refuel at station (5 minutes)	Refuel at station (7 minutes)	Refuel at a gasoline station (5 minutes)	Refuel at a "fast fill" station (15 minutes)
Refueling Time	1 minute	1 minute	9 minutes	15 minutes
Vehicle Range	400 miles	650 miles	700 miles	250 miles
Trunk/Cargo Space	271 cubic feet	221 cubic feet	132 cubic feet	61 cubic feet
Annual Maintenance Cost	$710	$511	$512	$655
Acceleration Rate (0-60 mph)	10.5 seconds	10.5 seconds	6.9 seconds	12.2 seconds
Select One	○	○	○	○

respect to the attributes mentioned in the choice set and they should be considered otherwise identical (all non-listed attributes like safety measures should be assumed to be identical across the options). The 4 X 14 choice set design for each of the eight experiments may have been demanding of respondents, and there is a possibility of fatigue while completing them. Though there is no real consensus in the literature on experiment design about the optimal number of choice sets, in general, most studies ask respondents to evaluate between one and sixteen choice sets, with the average being somewhere around eight choice scenarios per respondent [Louviere et al., 2000]. Exposing respondents to 5,7, and 17 choice sets in a discrete choice experiment eliciting preferences for dental services Bech et al. [2011] found no differences in response rates and no systematic differences in the respondents self-reported perception of the uncertainty of their answers. The SP survey used in this paper presented eight choice scenarios to each respondent.

The base model specification, with only the vehicle attributes from the stated preference tasks, accounts for the choices of 3,421 households who qualified and took the second round of the survey (Table 1.3).[2] In order to account for the effect of vehicle holdings on the transaction decision of a household and the effects of other demographics like income, family size, presence of children, and county of residence, the data from the CHTS and the CVS are linked. For the model specifications with household demographics and vehicle holding, only one-, two-, and three-vehicle households are considered. Hence, for the final analysis, I am left with 3,108 households[3]. Out of the 3,108 households there are 842 one-vehicle, 1,629 two-vehicle, and 637 three-vehicle households.

1.4 Model Specification

1.4.1 Conditional Logit Model

Vehicle choice decisions are characterized by a discrete outcome. The base model includes as covariates only the vehicle attributes that the households received in the choice experiments (Table 1.3). The next set of model specifications include details on vehicle ownership by fuel type and other demographics. As mentioned in the paper by Brownstone et al. [1996], the majority of the early papers on the adoption of alternate fuel vehicle focused on electric vehicles and modeled choice based on only stated preference data, neglecting household

[2] 10 households were dropped from the data because of the presence of dominated price alternatives or extreme refueling time in their choice sets.

[3] 267 households were dropped from the data as they had zero or more than 3 vehicles in their holding. Of the remaining 3,154 households, 46 of them were dropped due to missing data on income

characteristics or the current holding of the household. One of the first choice models to consider household vehicle holding was developed by [Train, 1986]. It is a hierarchical model of auto ownership and use, designed to forecast future vehicle demand. Based on this work, Brownstone et al. [1996] developed a micro simulation model using both stated and revealed preference data to forecast demand for alternate fuel vehicles conditioned on the current vehicle holding of the household. The paper discusses in detail most of the prior studies on choice models for alternate vehicles, including a detailed description of the hierarchical model by [Train, 1986] and [Hensher, 1992].

In order to incorporate the effect of the existing vehicle portfolio of a household on their future transaction decision, the model specification of the [Brownstone et al., 1996] paper is used here. The transaction decision is considered as a sequential process, with the current holding driving the next purchase, which updates the households' vehicle holdings for the next period, and then the updated holding influencing any future transactions. It is important to take into account this effect particularly for the stated preference set up used to collect the current data. The data from the survey is about the intended vehicle choice of each respondent conditional on their current holding. This makes it important to include the nature of the vehicle portfolio both in terms of body and fuel type as factors that may drive the choice of a vehicle option.

Given their current vehicle holding, every household can possibly take two actions: add or replace a vehicle. The intention to add or replace a vehicle is over the course of the next 5 years from the time of completion of the survey. This intended action is combined with the household's stated plans for their current holding (to keep, replace or dispose) in the following 12 months from the completion of the survey to deduce the possible action of the household : add/replace.

Modeling vehicle choice conditional on current holding suggests that transaction should be ideally modeled with a nested logit specification. The nested logit specification does not require the Independence of Irrelevant Alternatives (IIA) assumption and allows for correlation among the unobserved error component within a nest. For example, correlation among unobserved factors can be expected to exist for households deciding to replace (one of the possible nests) or add (another possible nest) a vehicle. We can expect that consumers may share some unobserved common characteristic that puts them in that particular nest.

Mixed logit can be also used to deal with potential consumer heterogeneity in vehicle transaction choice. Still it can be hard to eliminate correlation patterns that may arise due to shared unobservable characteristics among highly differentiated vehicle alternatives like light duty vehicles [Train, 2003]. One way of circumventing this problem is to model consumer decisions using multinomial probit. In the context of the German automobile market, Daziano and Achtnicht [2013] estimate a multinomial probit model with GHK simulator to allow for both consumer heterogeneity and error correlation in vehicle choice decisions. The multinomial probit model allows for a completely flexible covariance structure, allowing researchers to take into account any possible correlation pattern.

The conditional logit set-up assumes IIA. In other words, each choice or option is independent of the other. This independence implies that eliminating any options from the choice set would systematically change the estimation results. To test for the validity of the assumption, the Hausman specification test was performed dropping the fourth alternative from each of the choice sets for every household. Though, in certain choice experiments we could not accept the IIA assumption, conditional logit can be considered as a general approximation of the preference structure and a reasonable baseline model. Secondly, IIA violation is a serious concern when the model is being used for forecasting or scenario analysis. Currently, since the interest of the paper lies in studying the average preference pattern of individuals and the willingness to pay for different attributes of a vehicle, a conditional logit model with socio-demographic characteristics should suffice.

In conditional logit models, the utility U_{ij} provided by alternative j to individual household

i is given by :

$$U_{ij} = V_{ij}(x_j, z_i) + \varepsilon_{ij} \tag{1.1}$$

where V_{ij} is the deterministic component of the utility function depending on attributes x_j of alternative j and demographic or vehicle holding characteristics z_i of household i. ε_{ij} is the unobserved random component of the utility. Consistent with the multinomial logit set up, ε_{ij} is an independent and identically distributed extreme value type I random variable.

Under these assumptions, and given utility maximizing behavior, the probability that alternative j is chosen by household i is given by:

$$P_{ij} = exp(V_{ij}) / \sum_{j=1}^{J} exp(V_{ij}). \tag{1.2}$$

The models are estimated based on the assumption that the choice made by a household in each of the eight choice sets is independent and uncorrelated. Therefore, when all the choice sets are pooled together the error terms or the unobserved utility is assumed to be uncorrelated. Nevertheless, there can be learning during the process of completing each choice set or respondents may suffer from fatigue. If there is learning or fatigue, the error terms would be correlated and the estimated standard errors downward biased. In this scenario, a model specification controlling for the effect of learning should be applied.

1.4.2 Covariates: Choice Attributes

The deterministic component of the utility V_{ij} is linear in parameters.

$$V_{ij} = \alpha + \beta * Choice\ Attribute_i + \gamma * Choice\ Attribute_i * Household\ Characterictics_j + \epsilon_{ij} \tag{1.3}$$

The definitions of choice attributes and interaction terms included in the deterministic component are given in Table 1.2.[4]

While purchase price, fuel consumption per mile (gallons per mile), refueling time, and annual maintenance cost can be expected to have a negative effect on the choice probability, the relation should be positive for the number of models available, fuel infrastructure availability, and vehicle range. However, the vehicle range is split into categories like 0-250 miles, 250-350 miles, and more than 350 miles to consider potential non-linearity in the preference for the attribute. In a model specification where more than 350 miles is considered as the base category, a negative coefficient is expected, suggesting that people would dislike to move to a lower vehicle range.

Since the SP vehicle transaction choices is modeled conditional on the current holding of a household, attributes of the currently held vehicle should also be included to define more accurately the utility associated with different vehicle combinations. In other words, instead of directly using the SP vehicle price, the model should ideally include the net capital cost associated with any vehicle transaction. Net capital cost would include information about both the SP vehicle purchase price and the market value of the currently held vehicle/vehicles. Similarly, including net operating cost would help in a better model specification. The rationale behind using net cost/benefit variables in a transaction choice set up is that households not only compare the net gain/loss from the current vehicle transaction but also consider the value of the remaining holding [Brownstone et al., 1996]. However, unavailability of data on market value of the vehicles held by the respondents makes it difficult to calculate or use these net cost/benefit variables. Therefore, the vehicle choice model estimated in the current paper uses the SP vehicle price to capture price sensitivity of buyers in the purchase decision.

[4] Vehicle attributes like price of the vehicle option, refueling time, cost per 100 miles, and purchase incentive amounts (tax and rebates) have been scaled by a factor of 1000.

To analyze the preference for different fuel types, the different fuel alternatives are consolidated into four major categories: hybrids (including gasoline hybrids, diesel hybrids and CNG hybrids), new technology (including plug-in hybrids, only CNG, battery vehicles and the hydrogen fuel cell options), diesel/bi-fuel/flex fuel, and gasoline vehicles. Interacting with the different vehicle body types (Truck, Van, SUV, and Car), the coefficients indicate the preference for a particular combination of fuel and body type over a gasoline car.

The nature of the survey data does not allow me to study any alternative specific effects in the model. Vehicle options (body type and fuel type) are different for each individual in each experiment/choice set. As a result, it is not possible to include the specific effect of a body or fuel type directly in the analysis.

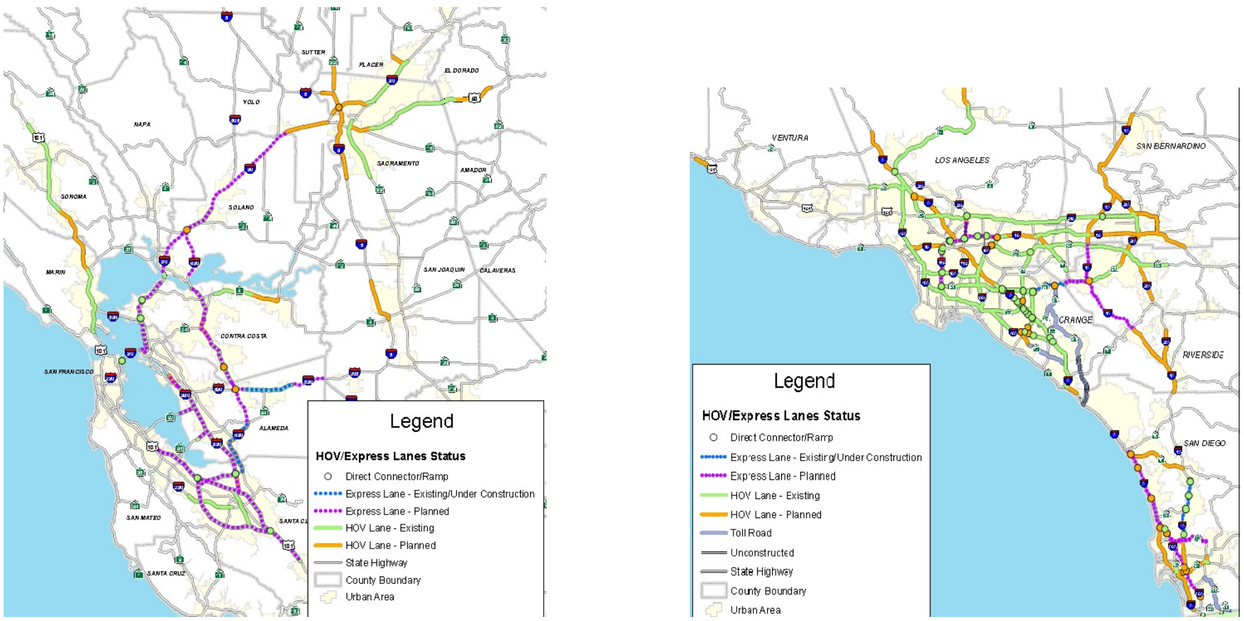
Most of the households in the survey have engaged in vehicle transactions before. Their prior knowledge about the new and used car market valuation may affect their response with respect to purchase price and other features. Consumers may be more aware of the market value of a used gasoline car than one with battery technology. Also, in spite of instructions to treat other features of the vehicle option as identical, respondents may attempt to figure out a connection between the model year, purchase price, and other attributes of a vehicle. To control for this effect, a dummy variable indicating the vintage of the vehicle option interacted with its fuel type is included in the model.[5]

Purchase incentives offered by the federal, state or local Government are targeted to promote adoption of alternate fuel vehicles. Therefore, a positive relation should be observed between purchase incentives and preference for low emission vehicles. However, the importance of HOV lane access or parking benefits can be closely related to the location and travel behavior of the household. For example, HOV lane access would most likely matter when offered to households located in regions with access and potential usage of HOV lanes. Figure 1.2

[5]Model specifications including the vintage of each vehicle option interacted with the price were also considered.

shows the maps of the HOV lanes in Northern and Southern California in 2012. According to the map, the current network of HOV lanes is concentrated only to regions adjoining major urban centers in the state like Los Angeles, San Francisco, and Sacramento. Similar to HOV lane access, parking maybe a concern only for individuals traveling to congested urban centers. To capture this effect, the usage-based incentives are interacted with the county of the household's residence.

Figure 1.2: High Occupancy Vehicle Lanes in California



(a) Northern California HOV Lane Map 2012

(b) Southern California HOV Lane Map 2012

1.4.3 Covariates: Household Demographics and Vehicle Holding

Accounting for household demographics, we expect to observe price sensitivity among individuals in almost all income groups. Also, family size can possibly influence the purchase decision of a household. A family of five can be expected to prefer a van or a SUV compared to a small or mid-size car.

Finally, the current vehicle holding of the household is taken into account. Different combinations of vehicles may offer different levels of utility to a household. For example, a household may derive higher utility from the combination of a car and a SUV than the combination of car and another car. Similarly, a household possessing a van is unlikely to purchase another van.

On the other hand, in terms of fuel type, the presence of an alternate fuel vehicle like Prius, Leaf, or the Volt may positively impact the choice of alternative fuel vehicles in the future. The current vehicle portfolio of a household in terms of fuel type also gives us an idea about their familiarity with a new technology or the preference for the same. Some of the households owning a Prius, Volt, or the Leaf are early adopters of the technology. Idiosyncratic preferences like greater environmental concern can make these early adopters more likely to purchase the electric battery or the HFC vehicles in future, or it can be state dependence/inertia. Though data limitations do not allow me to identify each effect separately, the results indicate that a household with alternative fuel technology vehicles in their portfolio is likely to continue to prefer a new technology vehicle. Ownership of an alternate fuel technology is captured by a dummy variable.

In the following section, two sets of results are reported. The first set corresponds to the model involving only vehicle attributes mentioned in the survey and including all the households with one-, two-, or three-vehicles. It is the conditional logit model with only SP choice attributes. The second set of results correspond to the model involving interactions with demographic and socio-economic variables and accounting for vehicle holding. A number of interactions that we can expect to impact choice of vehicle were tested: interaction between fuel type and income, time to refueling station and type of fuel, and vehicle type with fuel type. However, inclusion of some of these interactions led to loss of degrees of freedom without improving the explanatory power of the model. Hence, these interactions were dropped and only the ones that affected the explanatory power of the model and accounted for potential heterogeneity among the respondents are reported.

Table 1.2: Vehicle Choice Model: Definitions of Independent Variables

Variable Name	Definition
Vehicle Attributes	
Vehicle Price	Purchase Price (in thousands)
Cost per 100 miles	Fuel Expenditure to drive 100 miles
Gallons per mile	Fuel efficiency
Vehicle Range	Maximum travel distance with full tank or charge
Maintenance Cost	Annual cost to maintain the vehicle depending on miles traveled
Time to Refuel @ station (regular, or fast fill)	Time (in mins.) to get a full refill/recharge of the tank/ battery in a station.
Time to Refuel @ Home (<10 hours)	Dummy=1 if a full recharge of the tank/ battery at home takes < 10 hours
Time to Refuel @ Home (>10 hours)	Dummy=1 if a full recharge of the tank/ battery at home takes > 10 hours
Time to station	Time (in mins.) to reach the refueling station (Proxy for station availability)
Trunk Space	Cargo space in cubic feet.
Models Available	Number of other vehicles available for purchase with similar features
Acceleration Rate	Time to reach 60 miles per hour
Rebate	Amount offered with alternate fuel technology vehicles
Tax Credit	Amount offered with alternate fuel technology vehicles
HOV Lane Access Incentive	Dummy=1 if vehicle option has HOV lane access benefit
Free Parking Incentive	Dummy=1 if vehicle option has with free parking benefit
New_ Used Vehicle* New Technology Fuel	Dummy=1 interacted with CNG, HFC, and Battery
New_ Used Vehicle* Conventional Fuel Technology	Dummy=1 interacted with Gasoline, Hybrid, Diesel/Bi-fuels
Vehicle Body Type * Fuel Type [1]	Dummy=1 if the body type and fuel type combination is true. Gasoline car is the base category
Household Characteristics * Vehicle Attributes	
Income (<50 K)* Vehicle Price	Dummy=1 if income < 50 K* Vehicle price
Income (>150 K)* Vehicle Price	Dummy=1 if income > 150 K* Vehicle price
Household Size (> 4 members)* Vehicle Body Type [2]	Dummy=1 if household size > 4 and offered option Truck/Van
Household Education (> college graduation)* Hybrid fuel technology	Dummy=1 if head of household has college degree given hybrid vehicle option
Household Education (> college graduation)* New Technology fuel	Dummy=1 if head of household has college degree given new technology vehicle option
Household has children * Vehicle Body type [3]	Dummy=1 if household has children and offered the option of van/car/SUV
Residence County[4] * HOV lane access	Dummy=1 if residence is in specific county and offered HOV lane access benefit
Residence County[5] * Free parking	Dummy=1 if residence is in specific county and offered free parking benefit
Vehicle Holding * Vehicle Purchase Intention	
Alternate Fuel Vehicle Holding* Likelihood to purchase alternate fuel vehicle	Dummy=1 if household has Prius, Volt, Leaf, or other alternate fuel vehicle and gets the alternate fuel vehicle as option
Vehicle Holding (body type) * Likelihood to add a vehicle	Dummy=1 if household wants to add certain body type, given body type of holding vehicles. *e.g. 2 vans, 2 trucks, 2 SUVs*
Vehicle Holding (body type) * Likelihood to replace a vehicle	Dummy=1 if household wants to replace one of their vehicles *e.g. van with truck, SUV with SUV, or car with car*

[1] Body type includes truck, van, car, and SUV. Fuel type includes gasoline, hybrid, diesel/bi-fuel, and alternative fuel technologies
[2] Household size interacted with vehicle body types truck and van.
[3] Vehicle body types include van, car, and SUV.
[4] County of Residence (Southern California) include LA, Orange, San Diego, Riverside, San Bernardino. County of Residence (North California) include Alameda, Contra Costa, Marin, San Fransisco,Santa Clara, Santa Cruz, Solano, Napa, Sacramento, El Dorado, Placer,Yolo and San Mateo.
[5] County of Residence includes counties close to congested urban centers: LA, San Diego, Alameda, Contra Costa, Marin, San Fransisco, Santa Cruz, Sacramento, and San Mateo.

1.5 Results and Discussion

1.5.1 Model I: with only choice attributes

Estimation results from the regression model with only the attributes of the hypothetical vehicle options are given in Table 1.3.[6] The coefficient on purchase price indicates that a higher purchase price deters the choice of a vehicle. Considering that alternative fuel vehicles are often costlier than their gasoline counterparts, higher price may be an important explanation behind lower adoption rate for these vehicles. Secondly, fewer gallons per mile, lower cost of operation, and a higher vehicle range are preferred by potential car buyers. On the other hand, higher annual maintenance cost lowers the probability of vehicle choice. Maintenance concerns with respect to alternative fuels like battery or hydrogen cell may be higher, contributing to public skepticism. The technology is still in the process of development and vehicle parts are costlier and less accessible compared to gasoline vehicles. This difference raises maintenance concerns among potential adopters.

In terms of fueling infrastructure, a negative relation is observed between time to refuel or time to get to a refueling station and vehicle choice. Individuals prefer easy access to a fueling station and less time to refuel. Unavailability of fuel stations for alternative fuel vehicles is often cited as a main factor behind consumer skepticism regarding their viability. Also, due to the lower number of fuel stations for alternative fuels, vehicle range is a big concern for low emission vehicles. Along with the issue of low density of refueling stations, the full recharge time of a regular battery vehicle available in the market is 8-9 hours. In comparison, the refueling time of a gasoline vehicle is approximately 5 minutes (excluding wait time at the gas station). This inconvenience of higher recharge time can be a demotivating factor in the purchase decision.

[6] The results in Table 1.3 is based on the choice analysis of all the 3,421 households

Considering different fuel and vehicle body type combinations, it is observed that, households have a high preference for gasoline vehicles in different body types. The only other fuel and vehicle type combinations preferred to the base category, a gasoline car, are the hybrid car and SUV. The hybrid technology, first introduced by Toyota and Honda in 2000, has been in the market for a longer duration than any of the other non-gasoline options except diesel and bi-fuels. Thereby, the hybrid technology has been able to penetrate the vehicle market and build the required network effect to encourage adoption. In comparison, the preference for gasoline vehicles over battery, hydrogen fuel cell, or the CNG technologies may be because households are still skeptical about their viability and their skepticism is affecting the choice of these fuel options.

Since the introduction of the hybrid technology, tax credits, rebates, and usage-based incentives like the HOV lane access and parking benefits have been offered by the federal and state government to promote the adoption of new technology vehicles. Prices of these vehicles are still considerably higher than those of comparable gasoline vehicles, and tax credits and rebates help in offsetting the high initial adoption cost. Hence, as the results indicate, they have a positive effect on the likelihood of purchase of the alternative fuel vehicles. It is observed that the rebates (ranging between $500 and $2500) are valued more than the tax credits (ranging between $500 and $7500). A potential explanation of this result can be that households prefer an upfront reduction in purchase price via a rebate to a tax credit involving a wait for reimbursement. Usage-based incentives like the free parking benefit or the HOV lane access seem to positively affect vehicle choice. However, we can expect that the utility of these incentives would depend on the travel behavior and location of a household.

Table 1.3: Vehicle Choice Model Result- Base Model with only Choice Attributes

Variable	Coefficient[6]	(Std. Err.)
Vehicle Purchase Price (scaled by 1000)	-0.046**	(0.001)
Gallons per mile	-11.228**	(1.229)
Vehicle Range (0-250 miles)[1]	-0.453**	(0.032)
Vehicle Range (250-350 miles) [1]	-0.284**	(0.024)
Cost per 100 miles[2]	-0.025**	(0.002)
Refuel time @ station (in mins.)	-1.809**	(0.182)
Refuel Time @ home (<10 hours)[3]	-1.755**	(0.176)
Refuel Time @ home (>10 hours)[3]	-1.068**	(0.049)
Time to Refuel Station	-0.080**	(0.003)
Cost of Maintenance (scaled by 1000)	-1.967**	(0.090)
Trunk Size	-1.015	(0.656)
Acceleration Rate	-0.056**	(0.004)
Number of Models Available	0.015**	(0.002)
New Technology Fuel * New/Used Vehicle [4]	0.198*	(0.084)
Conventional Fuel * New/Used Vehicle [4]	0.027	(0.027)
Choice Attributes: Vehicle Body Type * Fuel Type[5]		
Truck * Gasoline (dummy)	0.282**	(0.087)
Van * Gasoline (dummy)	0.278*	(0.130)
SUV * Gasoline (dummy)	0.700**	(0.061)
Car * Hybrid (dummy)	0.268**	(0.070)
Truck * Hybrid (dummy)	-0.926**	(0.104)
Van * Hybrid (dummy)	-0.167	(0.140)
SUV * Hybrid (dummy)	0.721**	(0.085)
Car * New Technology (dummy)	-0.300**	(0.107)
Truck * New Technology (dummy)	-1.389**	(0.130)
Van * New Technology (dummy)	-0.938**	(0.161)
SUV * New Technology (dummy)	-0.304**	(0.117)
Car * Diesel/Bi-fuel/Flex (dummy)	-0.860**	(0.076)
Van * Diesel/Bi-fuel/Flex (dummy)	-0.908**	(0.150)
SUV * Diesel/Bi-fuel/Flex (dummy)	-0.098	(0.089)
Truck * Diesel/Bi-fuel/Flex (dummy)	-0.468**	(0.098)
Choice Attributes: Incentives		
HOV Lane Access Benefit	0.154**	(0.050)
Free Parking Benefit	0.068	(0.053)
Rebate (scaled)	0.130**	(0.032)
Tax Credit (scaled)	0.056**	(0.009)

[1] Vehicle range more than 350 miles is the reference category
[2] Gasoline price varies across household and options
[3] Refueling time are in minutes. The values were scaled
[4] New Technology Fuel include battery, hydrogen fuel cell, compressed natural gas, and plug-in hybrid options. Conventional fuel includes gasoline, diesel,gasoline-hybrid, bi-fuel, and flex-fuel vehicles
[5] For the vehicle body type * fuel type interactions, gasoline car is the reference category
[6] 1%:**, 5%:*, 10%†

1.5.2 Model II: with household and vehicle holding characteristics

1.5.3 *Model II(a): Household Characteristics*

Estimation results of models accounting for the effects of demographic factors and vehicle holdings of households are given in Table 1.4 and Table 1.5. The first set of results are based on the stated vehicle choice and characteristics of the 3,108 households in the sample. The second set of result captures the potential difference in preference of one-, two-, and three-vehicle households.

The effect of vehicle attributes on household choice is similar to the base model. All the factors except trunk size have the expected effect on household utility. Considering the role of incentives in vehicle choice decision, it is observed that rebates and tax credits play an important role in encouraging the market penetration of alternative fuel technologies by reducing the upfront cost of adoption. On the other hand, there is a strong link between the effect of usage-based incentives like HOV lane access or free parking and a households' location and potential access to these facilities. Households located around the Bay area, Sacramento, and in the Southern California counties have a positive valuation of the HOV lane access benefit and their choices are affected accordingly. Similarly, free parking matter to households making regular trips to congested urban areas with high parking costs. For example, compared to rest of California, households located near Los Angeles, Sacramento, or San Fransisco have a higher probability of making regular trips to the central business district (CBD) of these urban centers. Traffic congestion and high parking costs are some major problems associated with any trip to the CBD. Households living in these areas of California as a result, tend to have higher valuation for the usage-based incentives. Therefore, compared to tax credits and rebates, valuation of usage-based incentives is more clustered.

With gasoline car as the reference category, households with more than four family members and children state higher preference for large vehicles like the van. This preference pattern is compliant with their need for more seat capacity and trunk space. In terms of price sensitivity, household with annual income less than fifty thousand dollars prefer cheaper vehicles compared to those in the reference category.[7] On the other hand, households with annual income more than $ 150,000 are not price sensitive and have higher preference for luxury vehicles. Also, education raises the appeal for alternative fuel vehicles, as households with college-educated members are more likely to be environmentally aware.

Finally, current ownership of a hybrid, battery, or plug-in hybrid vehicle increases a household's likelihood to choose the new technology vehicles (there were 366 households with at least one alternative fuel technology vehicle in their holding). This relationship can be attributed to experience, inertia, or the personality trait of the decision maker in the household that make him more likely to adopt the latest technology. The diffusion process of any new technology involves a heterogeneous group of adopters, with the early owners of the technology being less risk averse or more technology-friendly than the late adopters. Likewise, in the case of alternative fuel technology vehicles, there is evidence of early adopters valuing different attributes of these vehicles compared to the rest. Using a dataset of voters in California, Kahn [2007] found that environmentalists are more likely to commute by public transit, purchase hybrid vehicles, and consume less gasoline than non-environmentalists. In order to account for this heterogeneity, an interaction term involving the years of ownership of the alternative fuel technology vehicle is included. Although this is a crude measure of potential heterogeneity, it captures the preference of early adopters of the hybrid technology. The positive coefficient on the interaction terms offer evidence of the heterogeneity observed among adopters of new technology vehicles.

[7] Households with annual income in the range $50,000 to $150,000 form the base category.

Table 1.4: Vehicle Choice Model Result- with Household Characteristics

Variable	**Coefficient**[9]	**(Std. Err.)**
Choice Attributes		
Vehicle Purchase Price (scaled by 1000)	-0.056**	(0.001)
Gallons per mile	-11.101**	(1.240)
Vehicle range (0-250 miles) [1]	-0.470**	(0.032)
Vehicle range (250-350 miles) [1]	-0.284**	(0.025)
Cost per 100 miles[2]	-0.026**	(0.002)
Refuel time @ station (in mins.)	-1.829**	(0.184)
Refuel time @ home (<10 hours)[3]	-1.760**	(0.179)
Refuel time @ home (>10 hours)[3]	-1.041**	(0.050)
Time to Refuel Station	-0.078**	(0.003)
Cost of Maintenance (scaled by 1000)	-1.926**	(0.091)
Trunk size	-0.437	(0.669)
Acceleration Rate	-0.057**	(0.004)
Models Available	0.014**	(0.002)
New Technology Fuel * New/Used Vehicle[4]	0.201*	(0.085)
Conventional Fuel *New/Used Vehicle[4]	0.088**	(0.027)
Choice Attributes: Fuel Type* Vehicle Body Type [5]		
Gasoline * Truck	0.219*	(0.092)
Gasoline * Van	-0.299*	(0.140)
Gasoline * SUV	0.634**	(0.063)
Hybrid * Car	-0.125	(0.082)
Hybrid * Truck	-1.315**	(0.116)
Hybrid * Van	-1.055**	(0.154)
Hybrid * SUV	0.284**	(0.096)
New Technology Fuel * Car	-0.721**	(0.116)
New Technology Fuel * Truck	-1.756**	(0.141)
New Technology Fuel * Van	-1.817**	(0.176)
New Technology Fuel * SUV	-0.725**	(0.126)
New Technology Fuel * Car	-0.845**	(0.077)
New Technology Fuel * Truck	-0.516**	(0.103)
New Technology Fuel * Van	-1.421**	(0.160)
New Technology Fuel * SUV	-0.158†	(0.091)
Choice Attributes: Incentives		
HOV lane Access Benefit	-0.035	(0.094)
Free Parking Benefit	-0.028	(0.068)
Rebate (scaled)	0.130**	(0.033)
Tax Credit (scaled)	0.058**	(0.010)
HOV Benefit *County of Residence (Southern California) [6]	0.185†	(0.108)
HOV Benefit *County of Residence (Northern California) [6]	0.274*	(0.107)
Free Parking Benefit *County of Residence [7]	0.197*	(0.084)

Table 1.4: Vehicle Choice Model Result- with Household Characteristics contd.

Variable	**Coefficient[9]**	**(Std. Err.)**
Household Attributes: Income, Size, Education, and No. of kids		
Income <50K * Vehicle Price	-0.003	(0.003)
Income >150K * Vehicle Price	0.023**	(0.002)
Household Size >4 * Van	0.402**	(0.111)
Household Size >4 * Truck	-0.122	(0.124)
Household Size >4 * SUV	-0.050	(0.065)
Children in Family * Van	0.716**	(0.153)
Children in Family * SUV	0.143	(0.132)
Children in Family * Car	-0.085	(0.129)
Education (college graduation and above) * Hybrid Technology	0.416**	(0.050)
Education (college graduation and above) * New Technology	0.354**	(0.055)
Household Vehicle Ownership: Alternate Fuel Vehicle Holding[8]		
Own New Technology Vehicle *Hybrid Vehicle	0.863**	(0.136)
Own New Technology Vehicle *Battery/HFCV/CNG/PHEV Vehicle	1.595**	(0.133)
Own New Technology Vehicle *Diesel/Bi-Fuel/Flex Vehicle	0.635**	(0.112)
Years of Alt.fuel vehicle ownership * Hybrid Vehicle	0.067**	(0.020)
Years of Alt.fuel vehicle ownership * New Technology Vehicle	0.057**	(0.020)

[1] Vehicle range more than 350 miles is the reference category

[2] Gasoline price varies across household and options.

[3] Refueling time is in minutes. The values were scaled.

[4] Alternative fuel technology include battery, hydrogen fuel cell, compressed natural gas, and plug-in hybrid options. Conventional fuel includes gasoline, diesel, gasoline-hybrid, bi-fuel, and flex fuel vehicles

[5] For the Vehicle body type * Fuel type interaction, gasoline car is the reference category.

[6] County of Residence (South California) include LA, Orange, San Diego, Riverside, San Bernardino. County of Residence (North California) include Alameda, Contra Costa, Marin, San Fransisco,Santa Clara, Santa Cruz, Solano, Napa, Sacramento, El Dorado, Placer,Yolo and San Mateo

[7] County of Residence include counties close to congested urban centers: LA, San Diego, Alameda, Contra Costa, Marin, San Fransisco, Santa Cruz, Sacramento, and San Mateo.

[8] New technology vehicle ownership include Volt, Prius, Leaf, Smart car etc.

[9] 1%:**, 5%:*, 10%†

1.5.4 *Model II(b): Vehicle Holding Characteristics*

The portfolio of vehicles in a household affect the future purchase decisions. Accounting for family size and number of children, households may want to replace their current vehicle or add to their portfolio vehicles that offer similar/comparable attributes to those of their current/last vehicle. In order to consider this effect, the model is specified separately for one-, two-, and three-vehicle households.[8]

If a household has the intention of adding a vehicle to their existing portfolio, then different combinations of vehicle types that might be considered, given the current holding are analyzed. For example, if a one-vehicle household already owns a car and has children, it is more likely that the household would want to add a van or a SUV to its portfolio. On the other hand, if the same household wants to replace its current vehicle, car, van, or a SUV is a likely substitute.

The results for the effect of vehicle holding in terms of body type on future transaction decisions should be interpreted with reference to the combinations of holdings that have not been included in the model specification. For example, in the case of new holdings (add a vehicle) for one-vehicle households, the combinations that have been left out are 2 trucks, SUV and truck, van and truck, and, car and van. In the case of replacement, the categories that have been left out to form the base specification are replace SUV with van, SUV with truck, van with truck, car with van and vice-versa. The results in column I, II, and III of Table 1.5, pertain to the vehicle choice models estimated on stated preference of 830 one-vehicle[9], 1,576 two-vehicle[10], and 558 three-vehicle households[11] respectively.

Vehicle attributes, factors affecting the operating cost of a vehicle, and demographic factors

[8]The model specification for more than three-vehicle households gets complicated, with many potential vehicle combinations. Also, the number of such combinations actually present in the sample may be too low for estimation.

[9]Out of 855 one-vehicle households in the sample, 12 of them had ambiguous purchase intentions in terms of add/replace. 13 households were dropped due to missing data on income.

[10]Out of the 1654 households, 13 households were dropped due to ambiguous purchase intentions (add/replace). Of the remaining 1,641 households, 40 households were dropped as they either had two trucks or vans or they were big households with few children of age less than 10. It was not certain if the household vehicles were used for residential purposes in the former case. For the latter issue, the households were dropped to avoid skewed preferences for large vehicles. 25 households were dropped due to missing income.

[11]20 households from the initial sample of 645 three vehicle households were dropped due to missing model year of the vehicle in the holding or ambiguous purchase intentions. 67 households were dropped as they either had two trucks, two vans, or all three trucks, three vans, or they were big households with few children of age less than 10.

like income, family size, education, and number of children have the same effect as in the earlier model specifications for the different types of households. Likewise, both tax credit and rebate program significantly affect the likelihood of purchase of new technology vehicles. On the contrary, except for two-vehicle households, there is no significant effect of HOV lane access or free parking benefit on utility; even when interacted with the county of the household residence. Multiple member households with only one vehicle may carpool on a regular basis, in which case HOV lanes in California can be accessed even when driving a gasoline vehicle. In this scenario, households may not put a high value on these incentives in the purchase decision.

Finally, the results under 'household attributes and vehicle ownership section' in Table 1.5 show that irrespective of the number of vehicles in the portfolio, prior ownership of alternate fuel vehicle like the Prius, Insight, or Volt, increase the likelihood of choice of a hybrid or any of the new technology vehicles.[12]

Table 1.6 shows the effect of vehicle portfolio on add/replace decision of one-, two-, and three-vehicle households. Conditional on the current vehicle stock of a household in terms of the body type, households with the intention to add a vehicle, show preference towards options with comparable or similar features and usage. A similar preference pattern is observed among one-, two-, and three-vehicle households. For instance, compared to the combinations that form the reference category, two or more cars or SUVs are preferred while, a van and an SUV is disliked. However, the positive coefficient on preference for two or more trucks or two or more vans is contrary to the kind of vehicle portfolio expected in a residential setting. Households who want to replace their current vehicle seem to prefer to continue with the same body type, replacing an SUV with a SUV or a car with another car. This can be considered as an inertia effect in terms of vehicle body type.

[12] 62 one-vehicle, 208 two-vehicle, and 88 three-vehicle households in the sample owned an alternate fuel vehicle.

Table 1.5: Vehicle Choice Model Result- with Vehicle Holding Characteristics

Variable	**1 Vehicle**	**2 Vehicle**	**3 Vehicle**
Choice Attributes	(I)	(II)	(III)
Vehicle Purchase Price (scaled by 1000)	-0.05**	-0.06**	-0.06**
Gallons per mile	-15.47**	-9.05**	-15.55**
Vehicle Range (0-250 miles)[1]	-0.55**	-0.45**	-0.39**
Vehicle Range (250-350 miles)[1]	-0.27**	-0.3**	-0.28**
Cost per 100 miles[2]	-0.02**	-0.03**	-0.02**
Refuel time @ station (in mins)	1.000	-1.94**	5.19
Refuel Time @ home (<10 hours)[3]	-1.99**	-1.94**	-1.69**
Refuel Time @ home (>10 hours) [3]	-1.25**	-1.1**	-0.67**
Time to Refuel Station	-0.08**	-0.08**	-0.06**
Cost of Maintenance (scaled by 1000)	-1.94**	-1.91**	-1.83**
Trunk Size	-0.161	-0.48	0.3
Acceleration Rate	-0.06**	-0.06**	-0.06**
Number of Models Available	0.01**	0.01**	0.02**
New Technology Fuel * New Vehicle [4]	0.40*	0.17	0.31†
Conventional Fuel * New Vehicle [4]	0.10†	0.11**	0.50
Choice Attributes: Vehicle Body Type * Fuel Type[5]			
Truck * Gasoline (dummy)	0.61**	0.59**	0.05
Van * Gasoline (dummy)	0.49	0.24	-0.47
SUV * Gasoline (dummy)	0.98**	0.82**	0.91**
Car * Hybrid (dummy)	-0.105	-0.11	-0.22
Truck * Hybrid (dummy)	-1.012**	-0.78**	-1.39**
Van * Hybrid (dummy)	-0.719*	-0.22	-1.38**
SUV * Hybrid (dummy)	0.70**	0.43**	0.58*
Car * New Technology (dummy)	-1.03**	-0.78**	-0.52*
Truck * New Technology (dummy)	-1.31**	-1.22**	-1.99**
Van * New Technology (dummy)	-1.29**	-0.90**	-2.44**
SUV * New Technology (dummy)	-0.58†	-0.58**	-0.38
Car * Diesel/Bi-fuel/Flex (dummy)	-1.04**	-0.83**	-0.53**
Truck * Diesel/Bi-fuel/Flex (dummy)	-0.39	-0.08	-0.41
Van * Diesel/Bi-fuel/Flex (dummy)	-0.66†	-0.68**	-2.44†
SUV * Diesel/Bi-fuel/Flex (dummy)	0.05	0.03	0.3
Choice Attributes: Incentives			
HOV Lane Access Benefit	0.15	-0.12	0.11
Free Parking Benefit	0.01	-0.10	0.04
Rebate (scaled)	0.05	0.13**	0.18*
Tax Credit (scaled)	0.06**	0.05**	0.07**
HOV Benefit * County of Residence (South California) [6]	0.11	0.21	0.16
HOV Benefit * County of Residence (North California) [6]	-0.041	0.39*	0.08
Free Parking Benefit * County of Residence [7]	0.09	0.37**	-0.01

Table 1.5: Vehicle Choice Model Result- with Vehicle Holding Characteristics contd.

	1 Vehicle	**2 Vehicle**	**3 Vehicle**
Household Attributes: Income, Size, Education, and No. of kids			
Income <50K * Vehicle Price	-0.01*	-0.01†	0.01†
Income >150K * Vehicle Price	0.02**	0.02**	0.02**
Household size >4 * Van	0.55†	0.15	-0.03
Household size >4 * Truck	-0.33	-0.31	-0.66†
Household size >4 * SUV	-0.07	-0.02	-0.34
Children in Family * Van	1.66**	0.96 **	-0.25
Children in Family * SUV	0.94*	-0.01	-0.59*
Children in Family * Car	0.56	-0.16	-0.99**
Education (college graduation and above) * Hybrid Technology	0.32**	0.43**	0.53**
Education (college graduation and above) * New Technology Fuel	0.39**	0.53**	0.1
Household Attributes: Alternate Fuel Vehicle Ownership[8]			
Own New Technology Vehicle * Hybrid Vehicle	2.38**	0.99**	1.24**
Own New Technology Vehicle * Battery/HFCV/PHEV/CNG Vehicle	3.29**	1.45**	2.06**
Own New Technology Vehicle * Diesel/Bi-Fuel/Flex Fuel Vehicle	1.94**	0.25	0.81**

[1] Vehicle range more than 350 miles is the reference category

[2] Gasoline price varies across household and options.

[3] Refueling time is in minutes. The values are scaled by 1000.

[4] New Technology Fuel include Battery, Hydrogen Fuel cell, only Compressed Natural gas, and Plug-in Hybrid options. Conventional fuel includes gasoline, CNG, diesel, and gasoline hybrid, bi-fuel, and flex fuel vehicles

[5] For the Vehicle body type * Fuel type interaction, gasoline car is the reference category.

[6] County of Residence (South California) includes LA, Orange, San Diego, Riverside, San Bernardino. County of Residence (North California) includes Alameda, Contra Costa, Marin, San Fransisco,Santa Clara, Santa Cruz, Solano, Napa, Sacramento, El Dorado, Placer,Yolo and San Mateo

[7] County of Residence includes counties close to congested urban centers: LA, San Diego, Alameda, Contra Costa, Marin, San Fransisco, Santa Cruz, Sacramento, and San Mateo.

[8] New Technology Vehicle ownership include Volt, Prius, Leaf among others

Note: 1%:**, 5%:*, 10%†

Table 1.6: Vehicle Choice Model- Effect of Vehicle Portfolio on Add/Replace Decision

Variable	Coefficient[1]	(Std. Err.)
One-Vehicle Household		
Add: keep existing Car * Car option	0.562†	(0.309)
Add: keep existing SUV * SUV option	0.044	(0.368)
Add: keep existing Car * SUV option	-0.031	(0.262)
Add: keep existing Van * SUV option	-0.931*	(0.400)
Add: keep existing Car * Truck option	0.549†	(0.283)
Replace: existing Car * SUV option	0.286	(0.252)
Replace: existing Car * Car option	0.862**	(0.146)
Replace: existing SUV * SUV option	1.235**	(0.218)
Replace: existing Van * Truck option	-0.718	(0.448)
Two-Vehicle Household		
Add: keep existing 1 or 2 Vans * Van option	0.919**	(0.351)
Add: keep existing 1 or 2 Trucks * Truck option	1.274**	(0.282)
Add: keep existing 1 or 2 Cars * Car option	0.535**	(0.127)
Add: keep existing 1 or 2 SUVs * SUV option	0.776**	(0.187)
Add: keep existing 1 or 2 Cars * SUV option	0.121	(0.144)
Replace: existing Car * Car option	1.211**	(0.144)
Replace: existing SUV * SUV option	1.298**	(0.166)
Replace: existing Truck * Truck option	0.759**	(0.191)
Replace: existing SUV * Car option	0.705**	(0.146)
Replace: existing Car * SUV option	0.612**	(0.170)
Replace: existing Van * Truck option	-1.363**	(0.260)
Three-Vehicle Household		
Add: keep existing 2 or 3 Cars * Car option	0.269	(0.230)
Add: keep existing 2 or 3 Vans * Van option	1.392	(0.938)
Add: keep existing 2 or 3 SUVs * SUV option	0.611†	(0.317)
Add: keep existing 2 or 3 Trucks * Truck option	1.542**	(0.535)
Add: keep existing 2 cars and 1 Van * Van option	1.438	(1.107)
Add: keep existing 2 cars and 1 SUV * SUV option	-0.623†	(0.321)
Replace: existing SUV * Car option	-0.567†	(0.318)
Replace: existing Car * SUV option	-0.322	(0.319)
Replace: existing Car * Van option	0.385	(0.346)
Replace: existing Car * Car option	0.190	(0.321)
Replace: existing SUV * SUV option	-0.193	(0.310)
Replace: existing Van * Van option	2.227**	(0.374)
Replace: existing Truck * Truck option	0.838*	(0.346)

[1] 1%:**, 5%:*, 10%†

1.6 Willingness to Pay for Alternative Fuel Vehicles

Technology diffusion happens only when consumers are willing to pay for it. In other words, accounting for the effect of different vehicle attributes and household characteristics on personal vehicle choice, it is important to know whether consumers need to be compensated to shift their preference away from conventional fuel vehicles or, they would adopt the new technology without any compensation.

The willingness to pay (WTP) measure represents the amount a respondent is willing to pay for an improvement in the attribute level such that the utility after the change in the attribute equals the utility before the improvement. Assuming the model is linear in parameters, the WTP for a vehicle attribute 'a' is given by,

$$WTP = -\beta_a/(\beta_{price} + \beta_{pi}) \tag{1.4}$$

$$pi = price * income\ categories(<\$50,000, \$50,000 - \$150,000, >\$150,000)$$

Table 1.7 gives the willingness to pay measures for improvements in vehicle range, reduction in cost per 100 miles, and switch to a hybrid, diesel, bi-fuel, CNG, battery or a hydrogen fuel cell vehicle (truck, van, car, and SUV) from a gasoline car. The results reported in the table must be multiplied by 1000 to get the willingness to pay measures in dollar terms. Table 1.8 shows the 95% confidence interval for the WTP estimates given in Table 1.7

Willingness to pay (WTP) for fuel cost has been discussed extensively in the literature on 'energy paradox' (Bento et al. [2012], Allcott and Wozny [2014]). The relevant null hypothesis is that consumers are willing to pay one dollar more to purchase a vehicle with one dollar less in total future fuel costs, discounted to present value. Considering the cost per 100 miles as representative of sensitivity to fuel cost, the corresponding willingness to pay measures indicate that households on an average are willing to pay $239 for every $1 saved in cost of driving 100 miles. Assuming a vehicle is driven for 10,000 miles a year on an average, the household is willing to pay this premium for a saving of approximately $100 per year. One-vehicle households with annual income less than $50,000 are willing to pay a premium of $118, while households with annual income over $150,000 would pay a premium of $88 for a $1 reduction in cost of driving 100 miles indicating lower cost sensitivity among the latter group. WTP for lower operating costs indicate that consumers are not myopic [Busse et al., 2013]. However, the estimate based off the conditional logit model may be biased because of unobserved heterogeneity in consumer groups with respect to fuel cost sensitivity [Bento et al., 2012].

In the case of vehicle range (in miles), one-vehicle households with income between $50,000 and $150,000 are ready to pay $5,643 to move from a vehicle that gives a range of less than 250 miles to a vehicle that offers a range above 350 miles. For every household type and income group, we observe that there is a natural non-linearity in the preference for vehicle range. Households are willing to pay a higher premium to move from a vehicle with range less than 250 miles to one with range above 350 miles, than moving from 250-350 miles to more than 350 miles.

For different fuel types, the willingness to pay is interpreted as the premium a household would want to pay, or the amount they would accept as a compensation to move from a gasoline car to an alternative fuel vehicle (car, van, truck, or SUV). The willingness to pay or the amount of compensation required for a switch to an alternate fuel vehicle from the gasoline car is given by:

$$WTP = -(\beta_{f,v})/(\beta_{price} + \beta_{p,i}) \tag{1.5}$$

$$p, i = price * income\ categories$$

$$f, v = fuel\ type * vehicle\ type.$$

WTP estimates for the one-, two-, and three-vehicle households indicate that they would have to be compensated to switch from a gasoline car to a hybrid technology vehicle in the range of $520 to $10,440 depending on the vehicle body type offered with the hybrid fuel. However, the households would be willing to pay an extra $630 to $7,000 to switch to a hybrid SUV from a gasoline car. The compensation required to move from a gasoline car to one with an alternative fuel, ranges between $1,000 to $7,000, depending on the income category of the household. The range of compensation amount is consistent with the rebates and tax credits currently offered by government agencies trying to promote alternative fuel vehicles. The amount of compensation is similar irrespective of the vehicle body type. The only exception is observed for three-vehicle households in higher income categories ($50,000 and above). If the gasoline car is a luxury vehicle in their portfolio, the high-income, multiple vehicle household may need a greater compensation to move to an alternative fuel truck or van with typically different usage characteristics, even if it is associated with lower operating costs.

For households with alternate fuel vehicles in their holding, the amount of compensation required for the different non-gasoline fuel and body type combinations is given in Table A.2 in Appendix A.2.

Table 1.7: Willingness to Pay Measures(unit: 1000 dollars)

Variables[1]		One Vehicle[2]			Two Vehicle[3]			Three Vehicle[4]		
		<\$50 K	Estimate \$50 K-\$150 K	>\$150 K	<\$50 K	Estimate \$50 K-\$150 K	>\$150 K	<\$50 K	Estimate \$50 K-\$150 K	>\$150 K
Cost per 100 miles in \$		0.118	0.242	0.087	0.044	0.306	0.264	0.034	0.211	0.228
Vehicle Range: 0-250 miles		2.760	5.643	2.039	0.661	4.640	4.009	0.597	3.687	3.999
Vehicle Range: 250-350 miles		1.376	2.813	1.016	0.431	3.028	2.616	0.422	2.604	2.826
New Technology CNG, HFCV, Battery	Car	5.163	6.144	3.815	1.131	1.318	6.862	0.791$^+$	0.586$^+$	5.298$^+$
	SUV	2.912	5.926	2.120	0.842	5.916	5.111	0.583$^+$	3.600$^+$	3.881$^+$
	Van	5.443	10.969	4.180	1.118	7.609	6.908	3.006	18.931	20.299
	Truck	4.366	9.607	3.626	1.346	8.864	8.318	2.382	14.103	14.584
Hybrid Fuel Technology	Car	0.523$^+$	0.623$^+$	0.386$^+$	0.154$^+$	0.180$^+$	0.937$^+$	0.340$^+$	0.252$^+$	2.280$^+$
	SUV	-3.497	-7.117	-2.546	-0.632	-4.442	-3.838	-0.880	-5.437	-5.862
	Van	3.032	6.108	2.328	0.274 $^+$	1.864$^+$	1.692$^+$	1.607	10.165	11.462
	Truck	3.381	7.439	2.807	0.864	5.692	5.341	1.659	9.830	10.165
Diesel/Bi-fuel/Flex Fuel	Car	5.225	6.219	3.861	1.209	8.470	7.340	0.806	0.596	5.395
	SUV	-0.274$^+$	-0.558$^+$	-0.199$^+$	-0.049 $^+$	-0.345$^+$	-0.298$^+$	-0.461$^+$	-2.846$^+$	-3.069$^+$
	Van	2.784	5.610	2.138	0.851	5.788	5.255	3.006	18.937	20.306
	Truck	1.321$^+$	2.906$^+$	1.097 $^+$	0.93$^+$	0.612$^+$	0.575$^+$	0.488$^+$	2.895$^+$	2.994$^+$
Gasoline	SUV	-4.896	-9.964	-3.565	-1.198	-8.417	-7.271	-1.371	-8.464	-9.125
	Van	-2.047$^+$	-4.125$^+$	-1.572$^+$	-0.295$^+$	-2.011	$^+$ -1.825$^+$	0.580$^+$	3.653$^+$	3.917$^+$
	Truck	-3.032	-4.485	-1.693	-0.650	-4.279	-4.015	-0.063$^+$	-0.376$^+$	-0.389$^+$

[1] Willingness to pay measures to be multiplied by 1000 to get the dollar amount.
[2] One Vehicle Household: Income range <\$50,000 have 249 households, \$50,000-\$150,000 has 471 households, and >\$150,000 has 110 households
[3] Two Vehicle Household: Income range <\$50,000 have 141 households, \$50,000-\$150,000 has 918 households, and >\$150,000 has 517 households
[4] Three Vehicle Household: Income range <\$50,000 have 36 households, \$50,000-\$150,000 has 293 households, and >\$150,000 has 229 households
$^+$ The coefficient on the fuel and body type combination for the corresponding type of household was not significant at 1,5, or 10 percent level of significance.

Table 1.8: Confidence Interval Estimates of WTP measures(unit: 1000 dollars)

		One Vehicle			Two Vehicle			Three Vehicle		
Variables		<$50 K	CI Estimates $50 K - $150 K	>$150 K	<$50 K	CI Estimates $50 K - $150 K	>$150 K	<$50 K	CI Estimates $50 K - $150 K	>$150 K
Cost per 100 miles in $		[0.07,0.17]	[0.13,0.35]	[0.05,0.13]	[0.03, 0.06]	[0.24,0.39]	[0.20,0.33]	[0.02,0.06]	[0.11,0.33]	[0.12,0.35]
Vehicle Range: 0 - 250 miles		[2.07,3.53]	[4.20,7.20]	[1.44,2.79]	[0.52,0.84]	[3.75,5.61]	[3.15,4.91]	[0.36,1.06]	[2.43, 5.10]	[2.57,5.59]
Vehicle Range: 250 - 350 miles		[0.87,1.94]	[1.75,3.19]	[0.61,1.54]	[0.32,0.56]	[2.26,3.73]	[1.95,3.29]	[0.24,0.76]	[1.47,3.67]	[1.61,4.01]
New Technology CNG, HFCV, Battery	Car	[0.08,0.25]	[0.08,0.23]	[0.02,0.06]	[0.62,1.65]	[4.50,11.22]	[3.98,9.84]	[0.62,1.65]	[-0.19,9.78]	[-0.21,10.70]
	SUV	[-5.83,-1.26]	[-0.08,12.29]	[-0.02,4.52]	[0.26,1.44]	[1.85,9.99]	[1.57,8.45]	[-0.37,1.74]	[-2.25,9.55]	[-2.52,9.96]
	Van	[2.01,9.04]	[4.12,18.37]	[1.56,7.13]	[0.51,1.82]	[3.46,11.91]	[3.16,10.80]	[1.75,5.31]	[11.55,26.77]	[12.60,28.84]
	Truck	[1.93,6.77]	[1.93,6.77]	[1.57,5.84]	[0.83,1.95]	[5.33,12.32]	[5.05,11.54]	[1.27,4.27]	[7.93,20.62]	[8.24,21.09]
Hybrid Fuel Technology	Car	[-1.07,2.10]	[-2.16,4.19]	[-0.82,1.50]	[-0.17,0.51]	[-1.20,3.45]	[-1.09,2.88]	[-0.22,1.08]	[-1.35,5.83]	[-1.48,5.99]
	SUV	[-5.83,-1.26]	[-11.85,-2.48]	[-4.49,-0.89]	[-1.13,-0.14]	[-7.59,-1.05]	[-6.61,-0.90]	[-1.91,-0.08]	[-10.01,-0.53]	[-11.05,-0.61]
	Van	[-0.11,6.28]	[-0.24,12.33]	[-0.08,4.91]	[-0.32, 0.91]	[-2.14, 5.87]	[-1.92, 5.47]	[0.57, 3.43]	[3.37,18.04]	[3.70,19.35]
	Truck	[1.60,5.34]	[3.56,11.57]	[1.34,4.63]	[0.39, 1.36]	[2.67, 8.73]	[2.53, 8.24]	[0.68, 3.06]	[4.40,15.63]	[4.47,16.08]
Diesel/Bi-fuel/Flex fuel	Car	[3.70,7.05]	[7.45,14.09]	[2.60,5.50]	[0.88,1.60]	[6.28,10.72]	[5.33,9.40]	[0.27,1.62]	[1.74,8.42]	[1.82,9.11]
	SUV	[-2.69,2.04]	[-5.34,4.03]	[-1.92,1.44]	[-0.49,0.39]	[-3.38,2.79]	[-2.90,2.42]	[-1.30,0.29]	[-7.40,1.87]	[-7.96,1.92]
	Van	[-0.33,6.01]	[-0.71,11.91]	[-0.27,4.77]	[0.22,1.50]	[1.68,10.06]	[1.54,9.02]	[1.56,5.31]	[10.74,27.53]	[11.80,29.56]
	Truck	[-0.34,3.05]	[-0.73,6.72]	[-0.28,2.52]	[-0.34,0.54]	[-2.24,3.40]	[-2.06,3.19]	[-0.38,1.54]	[-2.22,8.08]	[-2.27,8.41]

1.7 Conclusion

In the past couple of years, in spite of the introduction of more fuel-efficient gasoline vehicles and low gas price, the overall uptake of alternative fuel vehicles has gone up (www.hybridcar.com). Analysis of stated vehicle purchase decisions of households in California indicate that, in comparison to their gasoline counterparts, higher purchase price, longer refueling time, low-density of charging stations, high maintenance costs, and low vehicle range discourage uptake of alternate fuel vehicles. However, individuals do care about fuel efficiency, and they are concerned about gas prices. This is evident from the willingness to pay for lower cost of driving (cost per 100 miles). Therefore, even if there are more fuel efficient gasoline vehicles in the market, households looking for fuel cost savings in the long run would consider switching to the new technology vehicles as they get closer to their gasoline equivalent in terms of price and performance. Over the past few years, manufacturers have succeeded in improving the performance of these vehicles and lowering the price, making alternate fuel vehicles more competitive in the market. E.g. range of the new Chevrolet Bolt is over 200 miles and the price of the vehicle is below $35,000.

However, as the initial adoption cost (purchase price) of the alternative fuel vehicles will continue to be high in the near future, purchase incentives like tax credits and rebates would have to be offered to offset the price disadvantage and secure long term effects. However, the case of usage-based incentives is different. They have niche beneficiaries; only households with potential access and usage of the facilities like HOV lanes or free parking would value them in their purchase decision. Hence, these incentives can be more targeted, allowing efficient allocation of limited resources.

Finally, the paper sheds light on the relation between ownership of an alternate fuel technology vehicle and the likelihood to purchase another new technology vehicle in future. It is observed that households with a hybrid or battery vehicle in their holding are more likely to adopt a new technology vehicle compared to potential first time purchasers. Personality traits of the decision maker in the household may be driving the purchase intention. However, the likelihood to continue with new technology can also be considered as a sign of persistence or state dependence in preference patterns. Though brand loyalty may be a reason for this persistence, in the case of new technology vehicles, experience and learning would most likely prompt a repeat purchase. With experience, the skepticism associated with a new technology can be expected to decline. Hence, both price-based and usage-based incentives that reduce the initial adoption costs and induce experience are useful mechanisms to spur the adoption of alternative fuel vehicles.

Chapter 2

Policy Dilemma: Road Pricing or Road Space Rationing- A Case Study of Santiago, Chile

2.1 Introduction

A basic economic principle is that consumers should pay for the costs they impose on others as an incentive to use resources efficiently. Urban traffic congestion and vehicle emissions are often cited as examples. If road space is unpriced, traffic volumes will increase until congestion limits further growth and more trips would be undertaken than required, while if emissions are not taxed,vehicle owners would not have the incentive to invest in fuel efficient vehicles. For decades economists have recommended road pricing and emission taxes as a way to encourage more efficient use of the transport system, addressing congestion as well as pollution problems. However, proponents of pricing instruments have been frustrated at the political resistance they face in most cities.

Policymakers usually consider multiple travel demand management policies to deal with these externalities. However, the challenge is to meet the policy goal while taking into account the distributional concern associated with it. The gravity of the problem is higher in developing countries where a majority of the population is still in the middle- and low-income segments. Politicians are usually concerned that a tax or toll to correct traffic externalities would hurt all commuters, particularly the poor who spend a higher fraction of their income on transportation. Considering how voters may react to a rise in their daily commuting cost, they often resort to non-tax alternatives like a road space rationing policy.

Analyzing the mode choice decision of commuters and their demand response to different policy scenarios involving a vehicle mile tax[1], a cordon charge, and driving restrictions, this study examines the trade-off that policymakers face in their choice of mechanism to deal with traffic externalities. There is a compliance cost associated with all the policy options but the costs are different.

Studies on welfare effects of tax-based alternatives like congestion pricing have found that if a toll applies only to private auto trips, and there is an efficient redistribution mechanism to recirculate the revenue to improve the overall transportation network or lower labor taxes, the effect may be less averse for the commuters ([Parry and Bento, 2002], [Small, 1992]). Moreover, in the case of a developing country, low-income commuters tend to use the public transit system to commute to work. Hence, a congestion pricing scheme like cordon charges on auto drivers near the central business districts may affect the wealthy more than low-income commuters [Linn et al., 2016].

The choice of road space rationing to reduce vehicle emission and congestion is based on the idea that vehicle owners tend to belong to higher income groups. Therefore, the policy would affect only commuters from the wealthier segments and restrict their auto trip demand. In

[1] Vehicle mile tax can also be conceived as an area-wide pricing where a vehicle is charged for every mile they drive in a certain area.

reality, the effect of the driving restriction can also be heterogeneous both across and within income segments, particularly for the middle-income segment. While high-income households usually have multiple vehicles, those in the middle-income category may not always be able to invest in a second vehicle. Thus, the policy may have a differential effect on middle-income households depending on their ability to purchase multiple vehicles and access to other modes of transport [Gallego et al., 2013].

While reducing vehicle emissions is the main objective of the policy, one of its indirect goals is to encourage adoption of low-emission vehicles and make the vehicle fleet cleaner. The latter type of vehicles is commonly exempted from the driving restriction. In the medium and long run, there is evidence of fleet turnover towards cleaner vehicles [Barahona et al., 2015]. However, the main objectives of the policy tend to get invalidated as more vehicles get exempted. A brief review of the license-plate-based driving restriction policy practiced in some major cities of developing countries is given in Appendix B.1.

Past studies analyzing the driving restriction policy have primarily concentrated on the outcome of the policy. In most of the cities where the policy is implemented, including Santiago, the main aim is reduction in vehicle emissions of criteria pollutants namely, carbon monoxide, nitrogen oxide, VOC, and particulate matter. In almost all the cases, the Government introduces the policy with a short term goal and is successful in achieving the target to a great extent. However, as the restrictions are made permanent, commuters in the medium and long run adapt to bypass the restriction by purchasing multiple vehicles or by changing the trip time. [Davis, 2008] observed that sometimes the second vehicle purchased to avoid the restriction is old and more polluting. This spillover effect not only negates the objective of the restriction but can worsen air pollution. Policymakers have tried to contradict these behavioral changes of commuters by extending the restriction hours and exempting clean fuel vehicles while making the policy stricter for older cars. Overall, all the past analysis on the effect of driving restrictions on air pollution have concluded that the policy fails to reduce vehicle emissions in the medium and long run as people adapt to the restriction ([Lin et al., 2011], [Cantillo and Ortúzar, 2014], and [Sun et al., 2014]. The only exception is the study by [Carrillo et al., 2014].[2] [de Grange and Troncoso, 2011] studied the effect of the policy on vehicle flow in Santiago, Chile. The authors found that the policy is effective in reducing vehicle flow by 5.5% on days of environmental emergency when usually exempted vehicles are also restricted. On the other hand, in the case of Beijing, China, [Wang et al., 2014] failed to find any effect of the policy on auto demand and car flow.

Even though Governments choose policies like road space rationing based on welfare arguments, the literature has largely ignored the analysis of the incidence of the policy. To my knowledge, the only such attempt has been made by [Blackman et al., 2015], where the authors use a contingent valuation approach to calculate the costs of the driving restriction program in Mexico City. The paper focused on quantifying the incidence of the program by estimating the commuters' willingness to pay to get an exemption from the restriction. On average, a vehicle owner would be willing to pay roughly 1,000 pesos (approximately 121 USD) per year for a driving restriction exemption. Considering the fraction of their income a commuter would have to spend to get an exemption, the authors concluded that the policy is regressive.

Instead of considering the outcome of the policy, the present study aims to analyze the welfare cost of the driving restriction policy based on commuters' travel mode choice decisions and compare it with that of alternative tax-based instruments, namely, a vehicle mile tax and a cordon toll. The analysis is based on data drawn from the 2012 Travel Survey done in Santiago, Chile.

Mode choice decisions of commuters are analyzed using a discrete choice model-logistic regression. Estimates of consumer surplus loss reveal that driving restriction entails a compli-

[2] The authors found a positive impact of the driving restriction in terms of reduction in CO levels in Quito, Ecuador.

ance cost for commuters from all income groups but hurts middle-income commuters more than those from high- or low-income segments. The driving restriction policy scenario estimated here reflects the 'regular' restriction conditions whereby a certain fraction of only non-catalytic converter vehicles are restricted. As observed in previous studies [Gallego et al., 2013], high-income households tend to have multiple cars and can invest in clean fuel vehicles while low-income commuters tend to not use the auto option on a regular basis. It is the middle-income household that often has a single vehicle and high utility associated with it. Hence, the policy can hurt this segment of commuters the most. In the current study, the result is driven by the loss in commuters' utility due to the necessity to shift to transit from their private vehicles. Taxis are expensive in Santiago, particularly for longer trips. As a result, commuters from middle-income households may not find them affordable and are forced to choose the slower transit option.

The welfare effect that is measured here is the first-order effect of the driving restriction policy on 'general travel costs' of a commuter with limited transportation choices. The 'travel costs' would include the opportunity costs of time spent on travel by other modes, the direct pecuniary and non-pecuniary costs of travel. Comparing the incidence with that of alternative tax-based policies it is found that, for an equal reduction in total auto trips, the consumer surplus loss is higher for all the income groups. This is also a first-order effect of the pricing policies without taking into account the effect of reduced travel time on the utility of commuters and the presence of a revenue recycling mechanism. However, when the latter is taken into consideration whereby each commuter receives a lump sum transfer of the same amount, the consumer surplus loss is lower under road pricing than under the driving restriction policy. Unfortunately, if cities lack an efficient mechanism to recycle the toll revenue, the first-order effects are more probable.

Both vehicle mile taxes and a cordon charge are theoretically designed to address the congestion externality. However, one of the negative effects of congestion is vehicle emissions from stop-and-go traffic. Therefore, emission reduction is an important consequence of a drop in congestion [Currie and Walker, 2011].[3] Considering the rising motorization rates in developing countries and the positive relationship between congestion and pollution reduction, these two pricing instruments are chosen for comparative scenario analysis.

This study is not only relevant to the transportation policy scenario in Santiago, Chile, but also in other major cities of developing countries. In all the metropolitans where a city government considers the road space rationing policy, pricing instruments are also considered. Until this date, the latter set of alternatives have failed the distributional-concern test, so that policymakers resorted to other travel demand management policies. However, ongoing pollution concerns have compelled the governments in these cities to reconsider congestion pricing as a way to reduce driving in the affected regions. In this situation, it is important to have a comparative analysis of the welfare costs of these different policies under the constraints that are usually present in a developing country.

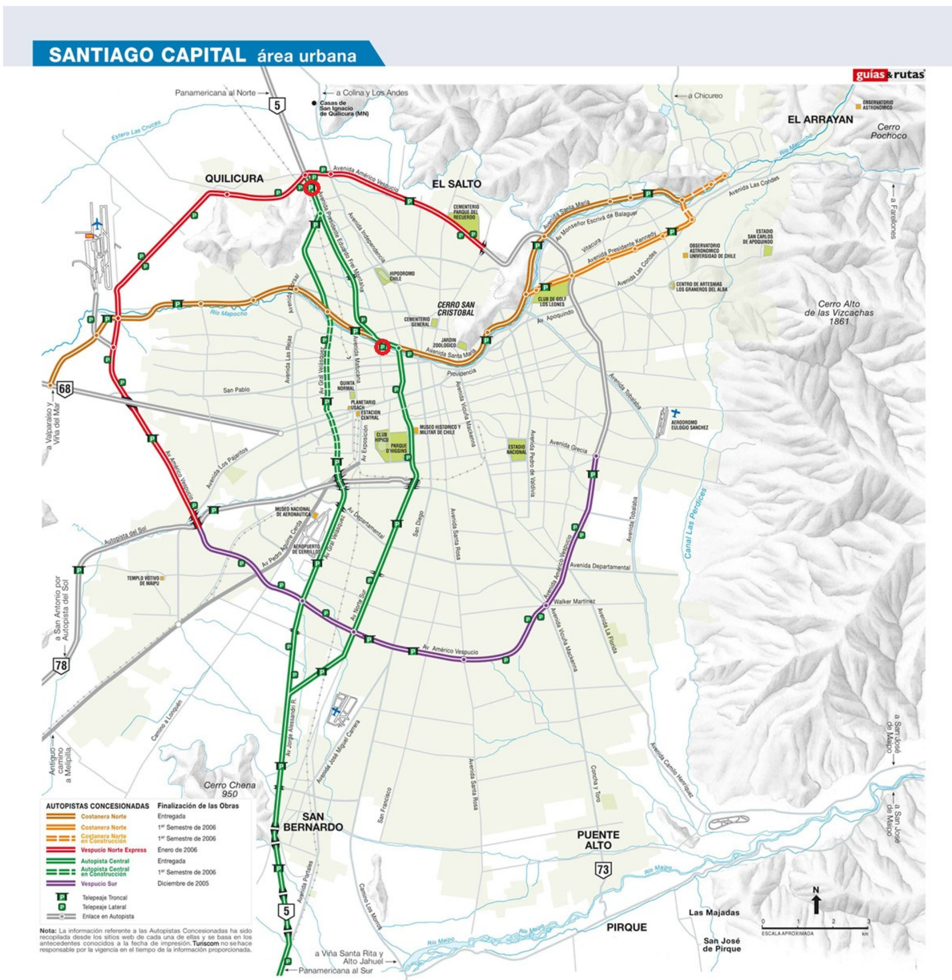
2.2 Background: License Plate Based Driving Restriction in Santiago, Chile

A driving restriction based on license plate number has been in place in Santiago Province, Chile since 1986. The city suffers from severe pollution problems due to its geographical setting during autumn and winter months when a thermal inversion sets in. The restrictions are traditionally in force from April through August every year for all four (or more) wheeled private motorized vehicles that do not have a green sticker, i.e. not equipped with catalytic converters (also called non-green seal [NGS]). According to the policy, if the license plate

[3] Analyzing the impact of reduction of traffic congestion on premature birth and low birth weight, [Currie and Walker, 2011] found that the introduction of the EZ Pass system in New Jersey decreased prematurity and low birth weight among mothers within 2 kilometers of a toll plaza by 10.8% and 11.8%, respectively, relative to mothers beyond 2 km from a toll plaza.

number ends with a particular digit and it is an NGS vehicle, then it cannot be driven on certain days of the week. Originally, the restriction was on 20% of the NGS cars, but in 2008 it was increased to 40% of the NGS fleet. The policy is effective on weekdays between 7:30 a.m. and 9 p.m. Weekends and holidays are exempt. From the beginning, the restriction

Figure 2.1: Santiago Metropolitan Region



applied to NGS vehicles only. One of the objectives was to encourage general upgrading to lower emission vehicles. To incentivize the turnover, a new decree was promulgated in 1991 which required any 1993-and-later models registered in Santiago and surrounding areas to be equipped with a catalytic converter (otherwise they could not be registered in Santiago) [Bauner and Laestadius, 2003]. These vehicles (also called green-seal (GS)) were exempted from the restriction. This encouraged households to buy cleaner vehicles. In their study on vehicle ownership and fleet turnover in Santiago, Barahona et al. [2015] found that households preferred 1993 cars over 1992 ones. This preference was primarily attributed to the nature of the driving restriction policy.

Increased car ownership over time and more exemptions implied that stricter restrictions were required to deal with periods when air pollution went beyond acceptable limits, described as 'critical episodes'. Depending on their severity, these episodes are classified as an alert, a pre-emergency, and an emergency.[4] On these days, a certain percentage of GS vehicles are also restricted along with an increased number of NGS vehicles. Since 2001, the additional restriction on pre-emergencies covered 20% of GS vehicles whereas the emergency restriction extended it to 40%. [de Grange and Troncoso, 2011] in their study of the impact of vehicle restriction on urban transport flows found that, the reduction in car trips on regular restriction days is negligible. A plausible reason for this result is that only 4% of the vehicle fleet of Santiago was non-green seal in 2012. Hence, 40% of 4% implies that a mere 1.6% of the vehicle fleet are affected by the policy on a regular day. However, vehicle flow reduction varies between 5-7 % on pre-emergency and emergency days. Even though the drop is larger, this reduction is lower than the target of 20-40%. There are multiple reasons why this might be the case: multi-vehicle households, a shift of travel demand outside the restriction period, or poor enforcement. Overall, even when enforcement is not perfect, the design of the driving restriction policy incentivizes ownership of cleaner vehicles while the old and more polluting ones are kept off the road. However, as motorization rate rises in the city, it necessitates other travel demand management strategies. The Government of Santiago, invested in a centralized public transit system in 2007 and tolled roads (private-public partnership) to deal with its rising traffic and its related externalities. There is also active consideration of policies like cordon charges and time-varying road pricing in high congestion areas.

[4]The pre-emergency days, emergency, and regular alert days are classified based on PM_{10} levels (ICAP scale). An emergency alert is declared when PM_{10} levels cross 200 ICAP. The Illness Costs of Air Pollution (ICAP) is an index to measure air quality and what associated health effects might be a concern for you.

Using Santiago, Chile as a case study, a structural model of travel mode choice is estimated to analyze the welfare cost of the driving restriction policy when mode availability is limited by the latter. Subsequently, the welfare cost is compared to that imposed by a vehicle mile tax and a cordon charge for an equal reduction in total car trips. The presence of the transit infrastructure and tolled roads enabled access to reliable data on public transportation and a baseline estimate of commuters' willingness to pay for time saving (toll rates).

2.3 Survey Details and Sample Formation

2.3.1 Survey Details

The data used for the mode choice analysis comes from the Santiago Origin-Destination Survey-2012 done by the University Alberto Hurtado for the Ministry of Planning and Cooperation and the Executive Secretary of the Planning Commission Investment in Transport Infrastructure (SECTRA, 2012). The objectives of the study were to (i) collect information required to characterize the patterns of urban travel and socioeconomic characteristics of travelers, (ii) conduct measurement of the flow and occupancy rate of the external cordon of the Santiago Metropolitan Region, (iii) measure the use and level of service of the public transportation system and the use of private vehicles, (iv) build databases and geographic information systems (GIS) using the information collected, and, (v) gather data on non-motorized travel.

The survey was conducted in 45 communes of the Santiago Metropolitan region.[5] Each commune was subdivided into multiple zones (a total of 876 zones in 45 communes). The zoning method of previous travel surveys was re-evaluated with the objective of including

[5]A commune is the smallest administrative unit. It is equivalent to a municipality. It may contain cities, towns, as well as rural areas. In highly populated areas, such as Santiago, Valparaíso and Concepción, a single commune may be broken into several sub-communes.

new areas of urban development into the study sample, namely, target areas for investment in the transportation system and other real estate developments.

The sample design for the survey used the method of probability proportional to size (PPS) with replacement[6] to select the clusters in a zone to be surveyed, where the size of each cluster was determined by the number of households in that block. Then, within each cluster, 'n' households were randomly selected. A surveyor contacted households in person with a cover letter. If the household consented then the surveyor gave them a questionnaire requesting demographic and vehicle holding information like age of respondent, income range, education, kind of vehicles in the household, vintage, and fuel type. For the questionnaire related to trip information, each household was randomly assigned a day of the week to record the information of every trip taken on that particular day. In the case of continued participation, the surveyor made a second visit to the household and collected the information in person. Each household and respondent in the sample were assigned raked weights based on the number of urban dwellings in that commune as recorded by the pre-census 2011 data, household size, and vehicle ownership.

The final survey dataset included 18,264 households. On the assigned day of the travel log, each household member had to enter the details of every trip they made on that day, including multiple stages in a particular trip. In total, there was mode choice data for 113,591 trips. The survey considered even children or very old people as possible commuters.

The survey was conducted between July 2012 and November 2013. Hence, the survey period includes both the phase when the road space rationing policy or the driving restriction is enforced in Santiago (July 2012-August 2012 and April 2013-August 2013) as well as the time period when there is no restriction (September-March)[7]. Descriptive statistics of the

[6]Probability proportion to size is a sampling procedure under which the probability of a unit being selected is proportional to the size of the ultimate unit, giving larger clusters a greater probability of selection and smaller clusters a lower probability.

[7]Since April 2015 the restriction has been made permanent for NGS vehicles

survey sample is given in Table 2.1. According to the income brackets defined in the survey document,[8] there are 1,165 high-income households, 10,098 middle-, and, 6,983 low-income households in the sample. In terms of vehicle holding, 11,067 households (60%) do not own any vehicle. 5,780 are single vehicle households (32%) and 1,399 (8%) have two or more vehicles.

Table 2.1: Descriptive Statistics- Demographic Characteristics of Survey Sample and Population

Attributes	Metropolitan Region Person=7,057,491	Survey Sample Person=46,266	Weighted Sample Person=6,651,700
Avg. Household Income(monthly)	USD 2548.2	USD 2,027.1	USD 2035.7
Avg. Income per capita	USD 857	USD 703.3	USD 701.2
Household Size		3.34	3.2
Number of Vehicles (non-Trailers)	1,597,762	8,887	1,160,700
Number of Green-Seal Vehicles (w catalytic converters)	1,533,885 (96%)	6,366 (71.63%)	835,704 (72%)
Median Age:	34 years	37 years	33 years
0-14 years	1,459,756 (20.7%)	7,618 (16%)	-
15-59 years	4,653,364 (65.9%)	31,071 (67%)	-
60 years & above	944,371 (13.4%)	7,551 (16%)	-
Gender (Male)	49%	48 %	49%

[1] Household income measured in Chilean Peso is converted to US dollar using a PPP factor of 347.2 (OECD, 2013)
[2] The weighted sample measures are based on the raked weights of the household used in the survey.

2.3.2 Sample Formation

The travel survey recorded the mode choice decision of each member of the surveyed household for all the trips taken on the assigned day. The respondents reported mode specific attributes like the fare paid in the case of public transit, taxi, or jitney, parking cost for their car, travel time, waiting time, and time to access the mode of transport among others. In addition, the survey also obtained data on demographics both at the household and individual level as well as details on the vehicle holdings.

[8]Income levels: $0-$1,152 is considered low-income group, $1,153-$4,608 as middle-income, and, $4609, and above as high-income. All income levels are expressed in US dollars.

According to the survey questionnaire, individuals could choose to drive a car or be a passenger, use the Transantiago system (bus, metro, or, both)[9], a non-TranSantiago bus (rural-urban or feeder bus), taxi, jitney, motorcycle, train, bicycle, walk, or any combination of these modes. Since children are also included in the survey, one of the reported mode choices was school bus. In order to analyze the data in the mode choice framework, the options are first consolidated into four categories: auto (as driver or passenger), public transit (Transantiago bus, Metro, non-Transantiago bus, and jitney), taxi, and non-motor mode (walk/bicycle). Since multiple modes could have been used in a single trip, in the absence of information on distance traveled by each mode, the categorization is done based on the mode used in the 'last mile'. Trips for which school bus (as passenger or driver), motorcycle, informal service, or the train were reported as the chosen mode are dropped from the sample used for analysis.[10]

Secondly, to model the mode choice decision of individuals, data is required on the mode-specific attributes of not only the chosen alternative but also for the other options available to an individual. In particular, data on cost and travel time is needed. External resources like the Google Distance Matrix API service, the Transantiago website, Comision Nacional de Seguridad de Transito (accident data), Ministry of Public Works website (toll rates), OECD reports, and previous studies on the transportation sector in Santiago have been used to impute the data for the non-chosen modes.

The following table gives the list of variables and the sources used for the data imputation process (Table 2.2).

Travel cost and time for the non-chosen modes were imputed using the following method:

[9] Transantiago is the centralized public transit system that operates in the Santiago Metropolitan area. It started operation in 2007.

[10] There is only one train route that is primarily used for commuting to the Metropolitan region and there were only 4 trips in the sample for which it was a chosen mode. Even if motorcycle is a common mode of travel in a developing country, any pricing or quantity restriction policy tends to exempt this mode of travel. Also school buses are exempted from restrictions as they serve a particular group of commuters only.

Table 2.2: Data Imputation for Mode Choice Model

Attribute	Mode	Source	Data imputed and its use
Cost of Travel	Auto	Google Distance Matrix	Distance; Calculate per mile cost of travel[1]
	Auto	Toll road websites	Per mile toll cost when toll roads used or available
	Auto	Sample data	Average parking cost by destination (Santiago or not)
	Transit	TranSantiago website	Fare for a trip
	Taxi	www.numbeo.com	Per mile fare
	Walk/Bicycle	National Committee for Traffic Safety (CONASET)	Cost of travel by non-motor modes
Time of Travel	Motor modes & Walk	Google Distance Matrix	Trip time for best route (peak time adjusted)
	Bicycle	Google Distance Matrix	Trip time for best route (no toll, no freeway option)

[1] Information on fuel cost is obtained from a 2013 OECD report

Cost of Travel

Auto: Google Distance Matrix service was used to obtain the distance traveled in miles for each origin-destination pair reported in the survey data. Only trips for which both the origin and destination coordinates were reported are considered. For trips with multiple stages, the distance between the final destination point and the origin is obtained from Google. Assuming an average fuel efficiency of 33 miles per gallon and a fuel price of \$3 for gasoline, \$2 for diesel, and \$4 for compressed natural gas, the per mile cost of travel by auto is calculated.[11] Vehicle ownership in Santiago involves an annual technical review and insurance cost. These fixed costs (per day) are added to the cost of travel by auto.

For the observed mode choice decisions, if the trip by auto involved a toll road, then the toll cost is added to the total trip cost. Respondents reported the name of the tolled road that they used during a trip. Assuming that the entire trip was completed using the tolled road, the toll cost was calculated as the per mile toll charged according to the time when the trip was taken times the distance between the origin and destination point (by auto mode). Trips where multiple tolled roads were used was dropped from the data used for analysis because there was no information on the points of entry and exit for the different tolled roads. When

[11] www.globalpetrolprices.com and Lopez-Global-Fuel-Economy-Initiative-Chile-Case-Study for average fuel efficiency of vehicles in Chile

'auto' is not the chosen mode, the toll costs were imputed using the predicted values of a linear regression model of toll amount on availability of toll road for an origin-destination pair, departure time, purpose of the trip, nature of the trip (long or short distance), and demographics like income and gender.[12]

If parking costs are reported, then they are added to the trip cost by car. When auto is 'not the chosen mode', then the average parking cost differentiated by destination of the trip has been added to the cost of travel.

Therefore, when auto is not the chosen mode, the trip cost by auto is calculated as:
Cost of Travel by Auto= Gallons per mile Cost per gallon * Distance + Fixed Cost + Average parking cost + Toll road cost (if available for O-D pair)*

When auto is the chosen mode, then the trip cost includes the reported toll value and parking charges.

Public Transit: The observed mode choice could include the TransSantiago bus system, Metro, rural-urban buses, the intra-city feeder buses, and jitney as public transit. The cost of travel is reported for only the non-TranSantiago options. Hence, the cost of travel by public transit when it is not the chosen mode as well as for the observed choices using the TranSantiago system is imputed using the fare information available on the TranSantiago website. The fares vary by the time of the day and the combination of bus and metro system used. During the peak period, the cost of a trip using the bus-metro combination is 740 Chilean pesos or US $1.11. The mid-peak rate is 660 pesos (US $0.99) and the off-peak cost is 640 Chilean pesos (US $0.96). The elderly (age 60 and above for women and age 65 and above for men) and students (middle school up to college degree studies) get a pass worth 210 Chilean pesos (US $0.315). These discounts are taken into account in the imputation process using the survey data on age and current educational status of each respondent.

[12]Toll road is considered available for a particular O-D pair if the origin and destination are within 3 miles of an entrance and exit to a toll road.

Shared Mode (Taxi and Jitney): The cost of travel by taxi when it is not the chosen mode is calculated using information on per mile taxi rate in the Santiago region and the distance reported by Google Distance Matrix for the origin-destination pair (auto mode).

Non-Motor Mode (Walk and Bicycle): There are no fuel cost, fare, or, parking cost reported for the non-motor modes. However, the risk associated with the usage of these modes can be monetized. Bicycle and walking are commonly used modes of travel in developing countries due to their lower operation cost compared to other motor modes. However, the risk of fatal accident associated with the mode when it has to share road space with auto and the transit system is high. 34% of the fatal accidents in Chile in 2015 involved pedestrians and 8% involved bicyclists. The exposure risk for pedestrians and bicyclists is calculated as the fraction of accidents in each category in 2012 to the total number of vehicle miles traveled (motor and non-motor). The total number of trips taken in the Santiago Metropolitan region on a particular day in 2012 was 18,461,100 (EOD 2012). Assuming the average trip length is 8 miles, the total number of vehicle miles was 147,688,800 miles. This implies that the risk of accident for pedestrians is 5.546 X 10^{-5} and that for bicyclists it is 2.223 X 10^{-5}. Considering the total cost of accidents was 404 million USD in 2013 (Road Safety Annual Report,2015)[4], the cost of road crash per mile is 2.735 USD. Hence, the expected cost for pedestrians (per mile) is 0.00018 USD and for bicyclists it is 0.00012 USD.

Since walking and the bicycle mode have been combined under one category, a distance rule is used to impute the cost of travel by the non-motor mode for each O-D pair (Zegras 1997). Based on the observed choice of mode, the distance rule was developed using a simple linear probability model of choice of non-motor mode as a function of distance of the trip. Walking is the chosen mode if the distance of the trip is less than 10 miles. The probability of choice of ‘walking’ as a mode falls beyond 10 miles and hence, for trip distances between 10 and 40 miles ‘bicycle’ is considered as the non-motor alternative. For trip distances beyond 40

[4]The cost of a road crash in Chile is calculated according to the Human Capital Approach.

miles non-motor mode is not available as an alternative (Bhatt 2000).

Travel Time

The travel time obtained from Google Distance Matrix for each origin destination pair is used for all the trips. In order to avoid reporting error in the data, the responses of the surveyed individuals are not used for the purpose of analysis. The travel time obtained from Google service is conditional on the traffic conditions at the time of query. In the case of peak period trips, the query was adjusted to account for potentially longer travel times.

Auto: Travel time for the auto option is extracted directly from Google Distance Matrix accounting for potential longer travel time during the peak periods of the day.

Public Transit: The travel time for the transit option is the sum of the time obtained from Google Distance Matrix service for the transit option and the average wait time estimated from the sample. As in the case of trips by auto mode, except for trips made during peak period, the travel time obtained from Google service is conditional on the traffic conditions at the time of query. In the case of peak period trips, the query was adjusted to account for potentially longer travel times.

Shared Mode (Taxi and Jitney): For the shared mode, the travel time by auto as obtained from Google Distance Matrix query for the origin-destination pair is used. The average wait time is added to the travel time.

Non-Motor Mode (Walk and Bicycle): Travel time when the chosen mode is 'walking' is obtained from Google Distance Matrix. However, in the case of Santiago, Google maps does not report time for the bicycle option. Hence, travel time is calculated using the distance by car with no freeway or tolled road usage (as obtained from Google) and assuming an average biking speed of 15 km/hr (9.3 miles/hr).

As a result of the data imputation, the final dataset has information on travel time and cost for all possible modes of travel for each member of the household (head of the household, spouse, kids, other relatives, domestic help). Only complete trips (multiple stages of the trip were collapsed) for which coordinates of both origin and destination were reported have been retained for analysis. This method of sample retention was required to get information on time and distance about the other modes from Google Maps. Secondly, households with no vehicles are not given the auto option as a driver or passenger. However, there were some individuals from households with no vehicle holding who had reported auto as the mode of travel. These individuals might have carpooled with friends or neighbors on the assigned day. Since this is a one-day travel diary, the usual mode choice decision cannot be ascertained for these individuals. Finally, only trips that were completed in the Santiago Metropolitan region were considered for analysis. As the majority of daily trips are undertaken in the Santiago Metropolitan Region, any transportation policy would primarily impact trips in this area.

2.4 Empirical Analysis: Mode Choice Model

The household and individual socio-demographic characteristics that are explored in the mode choice model include the income category of the commuter. The income categories were developed according to the OECD definition of ‘middle’, ‘affluent’, and, ‘disadvantaged’ income groups for developing countries. The lower and upper bounds of per capita income for the middle-income group are defined as 50% and 150% of median per capita income in the year of study. This method makes the group comparable across countries.

The mode choices available to a commuter depend on the vehicle holdings of their household, eligibility to drive, the purpose of the trip, and availability of transit options given the origin and destination of the trip. However, when there are more commuters than vehicles in the household, the decisions of the members are interdependent in terms of availability of auto as an alternative in the choice set. Though the data contains information on the mode choice of multiple members of the household for the trips they completed on the assigned day, modeling the choice of every member (head of the household, spouse, and kids) would require joint estimation of their mode choice decisions. The ordinary logit model is not appropriate in this scenario.

Moreover, if the household has two vehicles and there are multiple licensed drivers, it is not possible to allocate the vehicle to any one member without other information. Also, it is difficult to allocate mode alternatives under the driving restriction, particularly if the household has a combination of GS and NGS vehicles. A potential way of dealing with the vehicle allocation problem and availability of alternatives in the decision set of commuters is a random allocation of vehicles among the members in the household who are eligible to drive. Though this might give an idea about the effect of mode specific attributes on the choice decisions, the estimates of the market share of each mode or the distributional effect of altering any attribute of a mode may not be reliable.

Avoiding the interdependency in the mode choice decisions of a household and potential misallocation of alternatives, only the decision of the head of the household of zero and single-vehicle households has been modeled here, assuming that the head of the household gets the auto option when available. Moreover, as the mode choice of the first trip of the day would usually determine the choice of mode for subsequent trips (mostly they are round trips), only the first trip of the head of the household is considered. There is no doubt that this estimation strategy results in underutilization of information about the choice decisions of other members of the household. Also, it is fair to argue that the license-plate based driving restriction or any other policy would affect all members of a household. The current specification with the mode choice decision of only the head of a household cannot capture the total effect of a policy. In spite of these limitations, this model should still be able to capture the effects of mode and trip specific attributes on the choice decision as well as give a lower bound estimate of the change in consumer surplus under different policy scenarios.

Even though the survey covered both the time of the year when the license-plate-based restriction is enforced in the Santiago Metropolitan region and the period when there is no restriction, there is no information on whether a particular household vehicle was restricted on the assigned day of travel. Therefore, it was not possible to analyze the mode choice of the sample of households with vehicles surveyed during the restriction period. However, as households were randomly selected in both periods, it can be assumed that the preferences of the households surveyed in either period with respect to mode-specific attributes like trip cost, time of travel, accessibility, or convenience would be similar. Hence, the sample of households are split into two on the basis of the day/period of the survey and the final sample has zero-vehicle households from both the periods and one-vehicle households surveyed in the non-restricted period. In the absence of data on restricted vehicles for a particular household, this was done to avoid any misallocation of mode alternatives. Descriptive statistics of the final sample of head of household with zero or one vehicle is given in Appendix B.2.

The final model specification was developed through a systematic process of adding variables to a mode-specific-attributes-only model. This process was guided by intuitive reasoning, previous literature on mode choice behavior and parsimony in the representation of variable effects. All the cost measures in the data and those derived in the subsequent sections have been converted from Chilean pesos to US dollars using the OECD Purchasing Power Parity (PPP) conversion factor. [13]

2.4.1 Estimation Results

The results of the conditional logit estimation of the mode choice model are shown in Table 2.3. The closed form of the logit specification makes it straightforward to estimate,

[13]The PPP conversion factor measured in terms of national currency per US dollar was 347.2 in 2012

interpret, and use [Train, 2009]. The following table gives the effect of mode specific attributes namely, trip cost, travel time, and access time on mode choice decisions controlling for purpose of the trip, destination of the trip (central business district or not), day of the week, and income category of the household member. Non-motorized mode is considered as the reference category in the logit model. The cost of travel is multiplied by the

Table 2.3: Mode Choice Model- Head of the Household

Variable	**Coefficient**	**(Std. Err.)**
Trip Cost X High Income	-0.130**	(0.012)
Trip Cost X Middle Income	-0.143**	(0.009)
Trip Cost X Low Income	-0.206**	(0.024)
Travel Time	-3.548**	(0.092)
Time to Access Mode	-1.490**	(0.257)
Destination CBD X Transit	0.172*	(0.082)
Destination CBD X Shared Mode	0.567**	(0.179)
Destination CBD X Car	-0.721**	(0.124)
Purpose of Trip: Work X Car	-0.978**	(0.093)
Middle Income X Car	0.804**	(0.186)
High Income X Car	1.145**	(0.190)
Weekday X Car	0.107	(0.110)
Weekday X Transit	0.728**	(0.070)
Car/Auto	-1.782**	(0.226)
Transit	0.768**	(0.090)
Shared Mode (Taxi)	-2.656**	(0.122)

1 Trip cost measured in Chilean Peso is converted to US dollar using a PPP factor of 347.2 (OECD, 2013)
2 Travel time is in hours
3 Destination CBD imply trips to the commune of Santiago.
4 Low Income (0-USD 460), Middle Income (USD 461-USD 1,380), High Income (>USD 1,381). Incomes are monthly income.
5 1%:**, 5%:*, 10%†
6 Joint significance tests of the interaction term of income with mode and income with cost was done. The null hypothesis could not be accepted at 1% level of significance

household's income category to reflect differential cost sensitivity of households. While trip cost has a negative impact on choice for all income categories, head of low-income households are more cost sensitive than those in the middle- and high-income groups. For the transit and shared mode category, time of travel includes the in-vehicle travel time and wait time. The estimated coefficients on the cost and time components give information about the value of time. The value of time is the extra cost that a person would be willing to incur to save time.[14] The value of time saving for different income categories is given in Table 2.4. For the high-income group the average value of time saving ($/hr) is estimated to be $27.3 USD, $24.8 USD for the middle- income, and, $17.2 USD for the low-income group.

Table 2.4: Value of Time Saving by Income Category

Value of Time Saving in $/hr			
	High Income	Middle Income	Low Income
Value of Time (95% CI)	27.3 (22.9,33.36)	24.8 (22.24,27.75)	17.2 (14.09, 21.98)

Considering that in Chile the average household net-adjusted disposable income per capita is lower than the OECD average of USD 29,016 a year (for other developed countries), the value of time estimates are higher than expected. This finding can be caused by two factors. Firstly, the survey was done in the Santiago Metropolitan region, which has a higher concentration of high- and middle-income households than the rest of the nation. As observed in Table 2.1, the average monthly household income in the Santiago Metropolitan region is high and comparable to that observed in developed nations. Therefore, it may be not be surprising that the estimated value of time is also in the range observed in these countries. The average value of time for surface transport as estimated by the US Department of Transportation in 2013 was $24.5 (35%-60% of total earnings). Also, the model estimates the mode choice decisions for the first trip of the day. The first trip is usually undertaken to go to work or business and hence, the value of time savings may be higher. Secondly, the simple logit model may not be able to capture the high variation in the value of time in a particular income category, and a discrete choice model that allows a flexible distribution on income may give more reasonable estimates of the value of time savings. The accessibility to

[14]The value of time savings for each income group is given by the ratio of the coefficient on travel time and the coefficient on the corresponding cost term.

a mode is measured in terms of the time it takes to access the mode of travel. As expected it negatively affects the choice of a mode.

Though jobs have spread throughout the Santiago Metropolitan region over the past decade, the commune of Santiago is still one of the main business districts in the region. For trips with the central business district as the destination point, it is observed that public transit and taxi is preferred to a non-motor mode of travel but auto is not. This may be due to high parking costs in the business district or due to congested roads during peak hours. Also, Santiago is well-connected to the surrounding regions by the transit system via metro. These factors might disincentivize people from taking their car to the central business district (CBD). The same reason can explain the negative relation between work as purpose of the trip and choice of auto mode. It is observed that, on average, individuals are less likely to travel by auto to work compared to non-motor modes.

Considering the mode preference of different income categories, it is observed that a commuter from a high- and middle-income household has a higher preference for the auto option than other modes compared to the head of household from the low-income category. This result presents the scope for price-based policies like a cordon toll near the CBD or time-of-day based parking charges. A cordon toll or high parking fees at the CBD would affect the higher income individual driving into the CBD more than the average commuter using the transit system.

2.5 Policy Scenarios

Policymakers usually consider a range of policy options to deal with a problem. Tax-based policies that are popular among economists often fail to satisfy their welfare concerns, and as a result, other policy alternatives tend to be implemented. The license-plate-based driving restriction is one of those alternatives implemented, primarily based on the welfare argument.

The scenario analysis in this section aims to explore this welfare argument and verify whether the choice of policy is justified. Multiple studies have shown that the driving restriction policy does impose compliance costs on commuters. The latter may have to change their transportation choices as their choice set becomes limited. As discussed by [Blackman et al., 2015], since driving restrictions prevent a household from using their car on some days of the week, it may force a household to reduce or reschedule driving, increase travel by other modes with different travel times, sell its car, or buy another car. These adaptations are related to 'generalized travel costs', which consist of the opportunity cost of travel time, the direct monetary costs of travel, and non-monetary costs like inconvenience.

In the current study, the welfare impacts estimated from the scenarios capture only the first-order effect of the policy due to restricted travel options. It does not account for possible consumer surplus gains from reduced travel times when vehicle traffic is reduced. Likewise, it also does not include any welfare benefits from pollution reduction. The results of the scenario analysis should be interpreted accordingly.

In the scenarios with tax instruments, theoretically an appropriate combination of congestion charges and revenue use in improving transportation networks should be optimal [Small, 1992]. There should be a welfare loss (relative to the first-best) from any other policy. Though the current set-up does not account for any indirect effect of the tax scheme in terms of time-saving, revenue recycling in the form of lump sum transfer is incorporated in the model.

The welfare effect or compliance cost of a policy is measured in terms of change in consumer surplus from the base case scenario of 'no-policy' i.e. when there is no driving restriction or tax on driving behavior. The logsum difference of expected utility [Small and Rosen, 1981] gives the change in consumer surplus.

$$E(CS_i) = (1/\alpha)(\ln \sum_q e^{V_{iq}^1} - \ln \sum_q e^{V_{iq}^0}), \tag{2.1}$$

where i=individual, q=alternatives, and $\alpha = dV/dC$ or the marginal utility of money (assumed to be constant).

To illustrate the difference in welfare costs of the driving restriction policy and tax-based instruments for an equivalent reduction in car trips, three policy scenarios are simulated. The results of the scenario analysis are given in Table 2.5.

Scenario I: Driving restriction policy currently practiced in the Santiago Metropolitan region, whereby 40% of the non-catalytic converter vehicles are restricted on a particular day. In 2012, 96% of the fleet had a catalytic converter. Hence, the policy affected only 4% of the non-catalytic converter vehicles in the fleet, and 40% of 4% or approximately only 1.6% of the total vehicle fleet was restricted on a 'regular' day (63,877 out of 1,597,762 vehicles in 2012). In the sample of zero- and single-vehicle households considered here, 10% of the households had a non-catalytic converter car. The survey may have over-sampled households with non-catalytic converter cars and therefore, the estimates of consumer surplus loss obtained from the analyzed sample may be upward biased. The scenario is simulated by removing the auto option from 40% of the households with NGS cars. Consumer surplus reduction under this scenario is shown in Table 2.5 (Column I).

The pricing instruments that are considered here for a comparison of distributional effects are: area-wide pricing or a vehicle mile tax and a cordon charge in peak traffic areas of the region. These two policies are most popular among proponents of pricing the externality.

Scenario II: Vehicle mile tax targeting only auto trips in the Santiago Metropolitan region. The Santiago Metropolitan region has both toll and non-toll roads. The vehicle mile tax scheme analyzed here would differentiate between trips undertaken using tolled roads and those completed using surface streets. A commuter pays a vehicle mile tax only if they use the surface street. If they use the toll roads, then only the toll amount is paid for the trip. In this case, it is assumed that trips are completed using either surface streets or tolled roads. In reality, however, commuters may use a combination of the two road types.

Scenario III: Cordon toll system that require commuters to pay a fixed price to enter and drive in the communes of Santiago, Las Condes, and Providencia. Though Santiago is still one of the main business district, in the past two decades, job locations have spread to the other two communes. Hence, a large number of work trips require travel to one of these three regions. As a result, traffic jams and congested roads are severe problems in these areas. Also, the wealthier neighborhoods with high vehicle ownership are concentrated in this region.

A grid-search algorithm is used to estimate the vehicle mile tax and cordon charge required to induce an equal reduction in total auto trips as the driving restriction policy. The vehicle mile tax or area-wide price required to attain the same reduction in auto trips as attained with the driving restriction policy on a 'regular' day is estimated to be 20.5 cents per km.[15]. The cordon charge that would enable similar reduction in total auto trips is estimated to be $1.90. Past studies in the Santiago region have considered similar cordon toll values of $1.41, $2.83, and $5.66 to drive in specific regions and streets in the Metropolitan region [Bull, 2003]. The study showed that a toll value less than 500 pesos or $1.41 may not be enough to cause any change in driving behavior. The distributional impact of the pricing policies is

[15]The off-peak speed on a surface street is in the range of 28-30 km/hr while the off-peak rate for tolled roads when the average speed is above 70 km/hr is 18 cents per km. The semi-peak rate for toll roads is approximately 34 cents per km when the average speed is between 50-70 km/hr. During peak traffic hours the surface street speed tends to fall to 12-18 km/hr. During similar hours, as the speed on toll roads fall below 50 km/hr saturation rate of 52 cents per km apply. During peak hours, for a 5 km trip commuters are willing to pay approximately 52 cents per km to save 10 minutes.

given under Scenario 2 and 3 in Table 2.5 (column II(a) and III(a) respectively).

2.6 Discussion: Policy Implications

Under Scenario I with the driving restriction policy, reduction in consumer surplus is least for the low-income group and highest for the middle-income. Given the high cost of daily operation, the number of low-income commuters regularly using auto as the mode of travel is usually small in a developing country and therefore, the policy does not affect their utility to a large extent. But the change is high for the middle-income segment. As middle-income households mostly have a single vehicle and taxi is an expensive mode, driving restriction may force them to use the transit system leading to a higher loss in consumer surplus. However, there can be significant variations in the income level of households in the middle-income category in a developing country. This implies that the policy may have a heterogeneous impact on households in this income category depending on which end of the segment it lies. Further investigation is required to break down the impact of the policy on the middle-income category. The high-income households, on the other hand, may already have multiple vehicles and can usually afford to travel by taxi. This is a possible explanation for lower consumer loss on an average for this group compared to the middle income. In total, the reduction in car trips is only 3.4%, with the total number of vehicles in the sample affected by the policy on a particular day being 4% (128 of 320 NGS vehicles among a total 3,191 vehicles).

Change in consumer surplus under Scenario 2 and 3 indicate that, in the absence of revenue recycling,a vehicle mile tax would leave commuters from all the income groups worse off compared to the driving restriction scenario, particularly the high- and middle-income households. This is expected considering that vehicle ownership and choice of auto on a regular basis is more prevalent in these income categories. As households in the low-income

Table 2.5: Policy Scenarios: Distributional Implication

	Scenario 1	Scenario 2		Scenario 3	
	Driving Restriction	Vehicle mile tax		Cordon Charge	
	Column I	Column II		Column III	
Income Categories		No Revenue Recycle (a)	Revenue Recycle (b)	No Revenue Recycle (a)	Revenue Recycle (b)
High Income	-0.15	-0.52	-0.17	-0.33	-0.19
Middle Income	-0.16	-0.25	0.08	-0.11	0.01
Low Income	-0.01	-0.05	0.27	-0.03	0.09

[1] The median consumer surplus and the change in consumer surplus is in dollar terms
[2] The consumer surplus is calculated using the logsum measure by Small,K and Rosen.
[3] No Government intervention is the base case scenario. Consumer surplus changes are estimated with respect to the base case scenario.

strata tend to use the public transit and non-motor mode of travel, the loss in consumer surplus is less in comparison to the other groups but, higher compared to the driving restriction policy scenario. These results are reported in Table 2.5 column II(a). The loss in surplus measured here is a first-order effect of the tax policy. If revenue recycling is considered then the surplus loss under tax schemes is lower than those under driving restriction for all income groups. If the revenue collected from the tax is redistributed as a lump sum transfer with each commuter getting \$ 0.32, there is consumer surplus gain for the middle- and low-income commuters (column II (b)). Considering the high variation in earnings in the middle-income category for a developing country, it would be interesting to study in future work the potential difference in the compliance cost of this pricing policy within the middle-income category.

The cordon charges i.e. a fixed charge to enter or drive in a certain congested area, hurt the high-income category significantly more than the other two groups Table 2.5 (column III) though if the revenue from the cordon toll is redistributed as a lump sum transfer of the amount \$ 0.13, the consumer surplus loss is lower for all income groups compared to the scenario with driving restrictions. The areas with the cordon charge in the scenario analysis are primarily the wealthier neighborhoods with high vehicle ownership and propensity to drive. Similar results were reported in the simulation study done by [Linn et al., 2016] on congestion pricing in Beijing, China. A cordon toll imposed around the CBD of Beijing would affect the higher-income commuters more than other income groups. In an exploratory study of the prospects for congestion pricing in four Latin American metropolitan areas where traffic bans currently exist, namely Santiago de Chile, Mexico City, São Paulo, and Bogotá, analysis of a survey of transportation experts in the cities and historical data on implementation of travel bans by [Mahendra, 2008] revealed that equity concerns for low-income car drivers often cited in discussions on congestion pricing in developed countries are less applicable in developing countries. Instead a key concern is the lack of political will because it is people with relatively higher incomes and political influence who predominantly own and use cars in the cities.

Overall, the results of the scenario analysis reflect the dilemma policymakers face. Pricing instruments are economically efficient and may encourage more optimal allocation of resources. However, the welfare effect of the tax schemes is negative for commuters from all income groups, particularly for the high- and middle-income group. Though a redistribution mechanism that allows efficient recycling of the toll revenue, reduces the consumer surplus loss from the tax schemes, in its absence, the driving restriction policy imposes lower welfare concern than tax schemes. In other words, in the absence of a revenue recycling mechanism, a comparison of compliance cost in term of consumer surplus loss lends support to the choice of policy.

2.7 Conclusion and Future Work

In this paper, I examine the incidence of the driving restriction policy and compare it with that of price-based instruments, namely, a vehicle mile tax and a cordon toll using scenario analysis. A structural model of mode choice in a discrete choice setting is estimated to derive the changes in consumer surplus under different policy settings. The estimation was done using data from the 2012 Travel Survey conducted in the Santiago Metropolitan Region by the transportation department of the Government of Chile. In the absence of data from the transportation network of Santiago, the survey data is augmented with information on travel time by the different modes using external resources. While deriving travel time information from network data is the norm for such studies, the data used in this study, obtained from Google Distance Matrix API, reflects more accurate travel times for a particular origin-destination pair.

The conditional logit model is used to analyze the travel mode choice decision of commuters in Santiago, Chile. The dependent variable of the logit model is the mode choice decision of the head of the household with zero or a single vehicle in its holding, and the explanatory variables included trip- and mode-specific characteristics as well as socio-demographics attributes of the commuter. The estimates of consumer surplus are derived using the results of the conditional logit model.

Three policy scenarios were analyzed. First, a situation that reflects the current driving restriction policy practiced in the Santiago region, whereby 40% of the non-catalytic converter vehicles in the total vehicle fleet are restricted on a particular day based on the last digit of their license plate number. Secondly, a scenario involving a vehicle mile tax that would enable an equivalent reduction in car trips as the driving restriction policy was evaluated. Finally, the scenario with a cordon charge to enter and drive in the business districts of the Metropolitan region was evaluated. The estimated effects of the restriction and price-based policies are first-order in nature and does not account for possible consumer surplus gains from reduced travel times due to reduction in vehicle count. Likewise, it does not include any welfare benefits from pollution reduction.

The first-order effects reveal that, in comparison to the base scenario of 'no policy,' the driving restriction policy hurts commuters from middle-income households the most as these families may have only one vehicle used regularly for commuting. The cost of travel by taxi may be too high for a middle-income commuter, forcing him to use the transit system. However, the loss in consumer surplus is lower for all income groups in comparison to the scenario with a vehicle mile tax or a cordon charge for the same reduction in total auto trips as the driving restriction policy. The tax and the toll rate was estimated using a grid search algorithm. Though the loss of consumer surplus for the low-income commuters is higher in all the scenarios involving price instruments compared to the driving restriction, it is lower in comparison to other income segments. A plausible explanation for this result would be that the high cost of operation prohibits car usage for commuting on a daily basis. Thereby, none of the policies affect their utility from the auto option to a great extent.

Overall, in the absence of a revenue recycling mechanism, the driving restriction policy might be both politically more feasible than a tax system and better in terms of welfare impact. A revenue recycling mechanism can reduce the compliance cost and generate better welfare outcome than a non-price alternative. However, in a developing country, it might be difficult to convince voters of the existence of such a system. There is a fair chance that the revenue gets redirected to other sectors that does not affect the commuter or it is lost in corruption. Theoretically, another form of recycling is a reduction in labor taxes to compensate for the higher commuting cost due to road pricing. In a developing country where the majority of the population are in the informal sector, reduction in labor tax may not be feasible or effective.

The driving restriction program is practiced in other Latin American cities such as São

Paulo, Bogotá, and, Quito as well as in Beijing. Although the particular experiences of the different policy scenarios would differ across these cities based on their existing transportation infrastructure, mode choice patterns, and income distribution, the above estimates give an idea of why the driving restriction policy is considered a reasonable approach for addressing the difficult problems of urban congestion and air pollution. Also, as cities like Beijing are looking for additional policy measures to reduce auto trips to the city, the results from the scenario analysis offer an estimate of the compliance costs by income groups for the different policy options.

As part of future work on this topic, it would be interesting to look at the potential variation in impact within the middle-income group. Also, the current analysis does not model heterogeneity in the value of time-saving within an income group. A random coefficient model for travel time can capture the potential heterogeneity in value of time savings. Secondly, the current set-up models the choice decision of only the head of the household. In future, the model can be made more representative for zero and single-vehicle households by incorporating the choice of the spouse and the children conditional on the mode choice decision of the head of the household. This set-up would still assume that the head of the household gets the auto option when available. A random effect model of the mode choice decisions can capture the remaining correlation in the decision process.

Chapter 3

Time-of-use Pricing and the Environmental Impact of Electric Vehicle Charging Schedules

3.1 Introduction

In the recent years, renewable sources of energy have become an integral part of the resource mix used to generate electricity for residential and commercial purposes. The inclusion of wind-, solar-, and hydro-energy in the production system has led to a reduction in greenhouse gas emissions (GHG) from the grid system that historically depended on fossil fuels for generation. In 2016, the biggest drop in carbon dioxide (CO_2) emissions came from the United States, where emissions fell 3% or 160 million tons. The predominance of natural gas in the electricity production process and renewable power that displaced coal were the main reasons for the drop in emissions (IEA Report, 2017). While the environmental benefits of renewable resources continue to drive their integration into the system, the intermittent supply characteristic of these resources creates new challenges for utilities, planners, and policymakers.

Electricity produced from solar or wind energy is intermittent in nature and, due to limitations in battery storage technology, it has to be used the instant it is produced. This implies energy production can surpass demand during certain times of the day, throwing supply and demand off-balance. The issue of 'oversupply' is a central challenge to incorporating renewable energy into the grid and due to the limited ability to store the excess power, it is curtailed to maintain electric reliability. In the U.S., this problem is often discussed in the context of California.

Driven by the motive to reduce GHG emissions from electricity production, the state government has set the goal to meet 33% of its energy demand using renewable sources by 2020 and 50% by 2030. To achieve the GHG emission reduction goals from the power generation sector, policymakers aim to change the source of energy from coal to fuels with lower carbon intensity (like natural gas or renewable sources) and reduce the demand for power through programs like the energy star program or building codes. Transportation is the second leading source of GHG emissions in the United States after electricity production, accounting for about 32% of total CO_2 emissions (EPA 2015), the state has also invested in initiatives to reduce emissions from the sector. Policies and programs to promote the adoption of alternative fuel vehicles, primarily electric and plug-in electric vehicles (EVs/PHEVs) have been the main focus to reduce the carbon footprint from the transportation sector. However, this strategy to de-carbonize private transportation has created a quandary.

Though EVs have zero tailpipe emission, the vehicle has to be connected to the grid to be charged. This creates additional demand for electricity. Electricity rates in this scenario, play a crucial role in encouraging EV customers to charge their vehicles in an environmentally and economically efficient manner. Unfortunately, standard electricity rate plans like the tiered or block pricing structure do little to encourage optimal charging times. In fact, the time-invariant rates that are based on total energy consumption rather than the time of consumption may even discourage efficient charging practices. If households plug-in the vehicle during the regular peak hours in the evening, it not only increases the cost of production of electricity and the chances of shutdowns due to overload, the emission effects are adverse as power plants ramp up gas turbines to meet the extra demand.

Driven by the objective to minimize the cost of production and risk of overload, utility companies in California and elsewhere in the U.S. offer special time-of-use (TOU) rate plans to encourage EV owners to charge their vehicles at night when overall household demand for power is low and cost of electricity production is low. Though the cost minimization objective is satisfied by this strategy, the environmental effect is often debated. Depending on the energy source of the base load plant, the emissions from EV charging will be more or less than the emissions from an equivalent gasoline vehicle. Also, as the adoption rate of EVs and PHEVs progress, the current structure of TOU pricing can generate a new period of peak demand at night. If the additional load demand is met using carbon-intense resources like natural gas or oil, there is the possibility of EVs causing higher emissions than a comparable gasoline vehicle. However, compared to the tiered structure, TOU rate plans give utilities in California the opportunity to align demand with the supply cycle of solar energy, satisfying the additional load demand for vehicle charging as well as avoiding the issue of 'oversupply' and curtailment of solar energy.

This paper studies the impact of moving from tiered electricity pricing to a TOU rate structure on EV charging behavior and the environmental effect of the shift in terms of GHG emissions. Simulating a TOU rate plan with seasonal variation in the rates charged, the potential emission effects of aligning the TOU periods with the supply cycle of renewable energy sources in California is also explored. Assuming the current market share of EVs in the California ISO (CAISO) region, the main result of the study indicate that both the marginal and total emission of CO_2 is lower under a TOU rate plan than the current tiered pricing structure. Moreover, the analysis of marginal emissions under the simulated TOU plan provide insights about the importance of aligning the TOU periods with the availability of renewable resources, particularly in the case of California. As the availability of resources can vary significantly between the noon- 2 p.m. period and the 5 p.m.- 7 p.m. slot, putting them in the same TOU period may undermine the environmental benefits of consumer response to time-varying rates. In this study, due to data limitations, both the time slots are considered as 'peak' TOU period. As EV owners respond to TOU rates, though a reduction is observed in marginal emissions in the peak period, the result may be solely driven by low emission plants satisfying demand during the mid-day. Unless the TOU periods are defined carefully, to account for the supply of renewable resources like the solar energy, it will be hard to realize the benefits of moving to a time-varying rate structure. Finally, the analysis of consumer response to TOU rates and its environmental implication is done only for weekdays to capture the potential environmental benefits of daytime charging in non-summer months of the year, offering support to policies that encourage workplace charging.

There are several important caveats to the analysis of the effect of TOU rates on EV charging behavior and the environmental outcome provided in this paper. First, it only captures GHG emissions associated with charging the vehicles. It does not account for environmental externalities due to criteria pollutants that are an important component in the analysis of benefits of EV adoption. Second, the analysis is based on the current share of EVs and the state of the electricity grid in the years 2010-2015. Over time, as the share of EVs increase and more renewable energy resources are integrated into the grid, the estimates of marginal emissions may change. Finally, the estimates of consumer response to TOU rates are based on data from the service area of San Diego Gas& Electric (SDG&E) while the change in marginal emissions is analyzed at the level of the CAISO. The underlying assumption was that change in demand in the SDG&E area would proportionately affect demand at the ISO level, and since the CAISO is responsible for maintaining grid stability in the region, the rise in demand would affect emissions accordingly.

Keeping these caveats in mind, the main results of the paper show that there are environmental benefits of moving from the tiered pricing structure to TOU rates in the California ISO region. As the three main utilities in the region plan to move to the latter rate structure for all residential customers by 2019, the analysis presented here is timely. Moreover, as the result of marginal emissions in different TOU periods indicate, policymakers need to carefully define these periods and should consider different rates for summer and non-summer months to realize the full economic and environmental benefits of the change in the rate structure and the investment in renewable resources in the grid.

3.2 Background

3.2.1 Renewable Energy Resources and Time-of-Use Pricing

In 2016, California had the highest amount of solar electric capacity installed (18,296 megawatts) in the US, accounting for 48% of its total renewable energy capacity.[1] With the higher adoption of photovoltaic cells and growth of distributed energy network, the total share of mid-day electricity generation from solar energy has gone up, while displacing demand for power from the grid. The rise in mid-day electricity production using solar power along with the inability to store the energy has created a risk of 'oversupply' requiring curtailment to maintain grid stability.[2] Though the amount of renewable energy curtailed varies by season following changes in demand, approximately a total of 25,000 megawatt-hours (MWh) of intermittent renewable energy was curtailed in the year 2016.

[1]Renewable sources constitute 29% of CAISO's installed capacity(excluding hydro-energy). Installed capacity refers to the total amount of generation capacity, but does not reflect the total generation available for dispatch at any given time (CAISO).

[2]Most of the curtailment is economic solar curtailment. Economic curtailment is defined as the resource's dispatch upper limit minus its real-time market demand (RTD) schedule when the resource has an economic bid. Dispatch upper limit is the maximum level the resource can be dispatched when various factors are taken into account such as forecast, maximum economic bid, generation outage, and ramping capacity.

As the share of solar and wind continue to grow in the resource mix, the loss of energy due to curtailment is expected to increase.[3] Though curtailment helps to maintain grid stability, it can be inefficient for renewable energy producers investing in the technology. The extent of curtailment and the risk of 'oversupply' in the CAISO region is demonstrated in Figure 3.1. One implication of the seasonal variation in curtailment for the current paper (Figure 3.1(a)) is the need to study the emission cost by season to evaluate the overall environmental impact of daytime charging of EVs. While daytime charging can be beneficial during the non-summer months, in summer, vehicle charging at super off-peak hours of the night might be environmentally better.

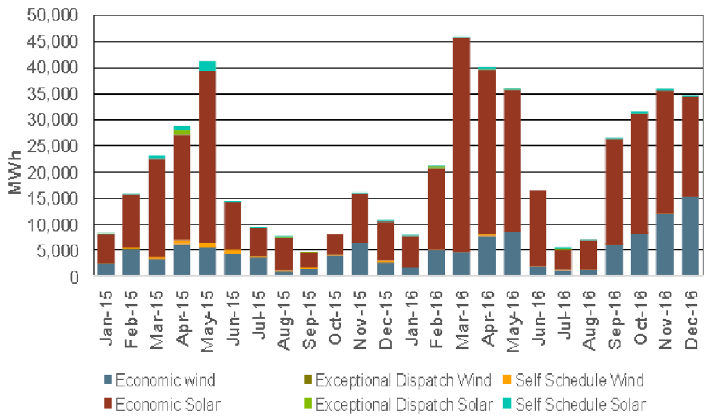
Along with curtailment, the rise in mid-day electricity production has caused the average hourly wholesale electricity prices to frequently drop to or below \$0 per MWh (Figure 3.2). Grid operators and planners are considering different approaches to deal with these issues- battery storage, vehicle-to-grid technology, and time-varying electricity pricing. Historically, pricing mechanisms have solely focused on shifting demand from the 'peak' periods, i.e., the times when supply is constrained and marginal cost is highest to off-peak hours, minimizing the cost of production of electricity. However, with the introduction of renewable sources, there is need to alert consumers not only of times when supply is constrained but also when there is a surplus, to provide incentives to consumers to take advantage of low-cost electricity, lower the loss of renewable energy providers,[4] and maximize the benefits of clean energy sources.

Recent studies by the CAISO, the largest ISO in the Western Interconnection reveal that planners are actively considering to match the electricity pricing structure with grid conditions to maximize the use of renewable energy sources. The TOU pricing structure proposed for the CAISO region is provided in Figure 3.3. Except for July and August, the time period

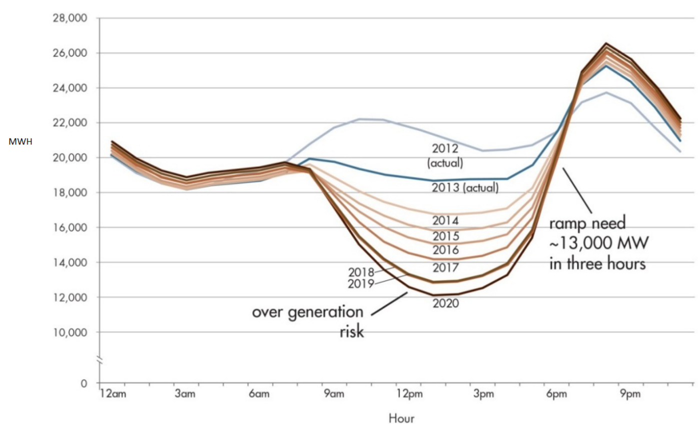
[3] In early 2017, CAISO announced that it could face a record-breaking need for curtailments - paying, or forcing, generators to stop pumping electricity into a transmission grid that just doesn't have the demand for it at the time. CAISO predicted 6,000 megawatts to 8,000 megawatts of curtailment in 2017.

[4] The loss depends on the nature of contract with the utility company and the balancing authority.

Figure 3.1: Changing Shape of Net Load Demand and Renewable Energy Curtailment
Source: California ISO



(a) Curtailment of Renewable Resources, California 2015-16

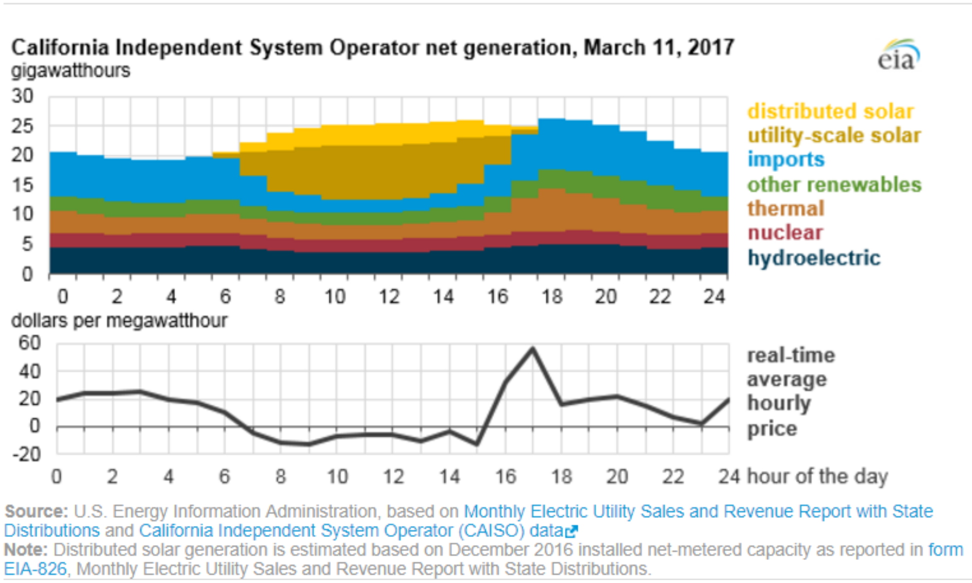


(b) Duck Curve: Difference between Gross and Net Demand

of off-peak and super off-peak hours during the day overlap with the time period when solar energy is at its peak.

In the past few years, a major change in household demand for power has originated from the adoption of EVs and PHEVs. While the adoption of energy efficient devices and smart meters will reduce household energy consumption, EV charging is expected to raise demand significantly in the future (Brattle, 2016). Using the pricing mechanism, if some of the load demand can be shifted to the hours when supply of renewable energy is high, there is

Figure 3.2: Negative Wholesale Electricity Prices (Source: California ISO, 2016)



potential to amplify the environmental benefits of EV adoption while efficiently integrating the extra demand into the grid, avoiding creation of new peak charging hours and the need to build more capacity and transmission infrastructure. Individual utilities like the San Diego Gas & Electric (SDG&E) and Southern California Edison (SCE) have pilot programs featuring special rates that encourage EV drivers to charge their cars when there is spare capacity, particularly solar power, and when energy prices are low.

While there is significant literature on the effect of electricity pricing on residential consumption behavior, there is a limited number of studies on TOU rates and its potential to generate environmental benefits both from the demand and supply side of the electricity market. Moreover, as the implementation of the pricing structure is mostly in the experimental phase, large-scale data on consumer response to TOU rates is not available. Using a unique data set of electricity usage by EV owners in response to TOU rates, the current study demonstrates the potential environmental effects of implementing the pricing system to align load demand due to EV charging with the supply cycle of solar energy in the CAISO region.

Figure 3.3: Proposed Time-of-use Pricing Structure: California ISO Region

Day-type	Months	Super Off-Peak	Off-Peak	Peak	Super Peak
Weekdays	Jan, Feb, May, Jun, Sep, Oct, Nov, Dec	–	Midnight – 4 PM 9 PM - Midnight	4 PM – 9 PM	–
	Mar & Apr	10 AM – 4 PM	Midnight – 10 AM 9 PM - Midnight	4 PM – 9 PM	–
	Jul & Aug	–	Midnight – Noon 9 PM - Midnight	Noon – 4 PM	4 PM – 9 PM
Weekends & Federal Holidays	Jan - Jun & Sep - Dec	10 AM – 4 PM	Midnight – 10 AM 9 PM - Midnight	4 PM – 9 PM	–
	Jul & Aug	–	Midnight – 4 PM 9 PM - Midnight	4 PM – 9 PM	–

3.2.2 EV Adoption and Emissions from the Grid

Utilities use different generating resources to produce electricity in increasing order of their marginal costs. The energy source of the marginal power plant used to meet the additional demand for EV charging determines the emission costs or benefits of driving the vehicle. When a region meets the additional demand with supply from a natural gas plant, GHG emissions are lower compared to a region where electricity is generated from a coal plant. Moreover, not all plants are operational throughout the day. While coal and nuclear plants usually operate all day to meet the base load demand, natural gas plants are turned on during hours of peak demand. Similarly, intermittent sources of energy like the solar or wind are available only during a particular time of the day. In other words, the marginal emissions of CO_2 from the power sector due to EV charging depend on both the location and time of the charging event [Zivin et al., 2014]. Considering both global and local pollution due to EV driving, the analysis of Holland et al. [2016] reveals similar results - significant spatial heterogeneity with California experiencing a benefit of 3.2 cents per mile, while in North Dakota driving an EV can impose a cost of 3.1 cents per mile.

Both Holland et al. [2016] and Zivin et al. [2014] apply a regression-based approach to study the environmental effects of driving an EV. The regression model offers estimates of benefit or cost based on the current share of EVs and the present characterization of the grid structure. However, as EVs gain market share and more renewable energy sources are incorporated into the grid, there is need to consider a model that allows a flexible characterization of demand and supply scenarios to evaluate the emission effects. In their study on short- and long-term environmental implications of PHEVs, Stephan and Sullivan [2008] note that in the long run larger share of PHEVs will decrease the average emissions from the total vehicle fleet, while future emissions from the grid due to additional load demand from EVs will depend on policies like carbon tax and CO_2 emission restraint programs. In this scenario, a dispatch model that can map the response of utilities to extra load demand taking into account changing grid conditions, transmission constraints, ramping needs, and other emission restraints on power plants can provide a more accurate estimate of the long-term environmental effects of EV charging behavior.

Using the EDGE-CA model, McCarthy and Yang [2010] investigated the response of the California grid to an added vehicle and fuel-related electricity demand and its sensitivity to the time of day and season. Though the merit-order approach of the model offers a higher level analysis of the impact of demand on supply and emissions than a regression model, unlike a grid dispatch model the former cannot account for the operational complexities involved in the dispatch decision. Improving upon both the regression based and the merit-order approach, as well as relaxing the assumption of a constant market share of EVs, Hadley and Tsvetkova [2009] used the Oak Ridge Competitive Electricity Dispatch Model (ORCED) to simulate multiple load demand scenarios and analyze the environmental and operational impact of PHEV charging.

In the current draft of the paper, the analysis is done using panel data models similar to Zivin et al. [2014] and Holland et al. [2016]. As a result, the estimates of marginal emission provided here are subjected to the assumptions and shortcomings of a regression-based model. Moreover, unlike the former studies here it is assumed that all the demand for energy is met by power plants in the CAISO region.[5] In future extensions of this paper, analysis of the environmental effect of additional load demand under alternative time-of-use pricing scenarios will be done using the ORCED model. Unlike the regression-based approach, a dispatch model will allow me to incorporate electricity trading into the analysis and calculate a number of key regional market outputs like the average and marginal price of electricity, emissions, and generation adequacy.

3.2.3 Utility Pricing Strategy and Consumer Response

Electricity rates play a crucial role in fostering the adoption of EVs and encouraging EV owners to charge their vehicles in an environmentally and economically efficient manner. Unfortunately, standard electricity rate structures like block pricing do little to encourage optimal charging times. In fact, time-invariant rates may discourage efficient charging practices since the super off-peak hours are not the most convenient time to shift energy usage.

Planners and practitioners have traditionally considered market-based solutions to control EV/PHEV charging: time-of-use rates (TOU), critical peak price (CPP), or real time pricing (RTP). Under such a scheme, charging decisions are left to households, but electricity tariff structure is designed to encourage EV/PHEV owners to charge at a time such that the cost minimization objective is met. For instance, a TOU rate, which charges a lower price for energy during certain hours of the day, provide EV owners with an incentive to delay vehicle charging from the early evening, when they arrive home, to overnight hours. CPP encourages

[5]Electricity trading happens at the interconnection level which would be the Western Electricity Coordinating Council for the CASIO region. In other words, load demand in any one region can be met by energy supplied from any plant in the interconnection. When the study area is concentrated to a sub-region it is important to account for trading. Otherwise, the results would be biased. The direction of the bias will depend on whether the sub-region is import- or export-heavy and the carbon-intensity of the resource traded.

households to reduce power usage during peak hours by charging a higher price during those hours. RTP, which dynamically sets prices based on the real-time marginal cost of energy, can provide EV owners with even more accurate price signals.

Contrary to economic intuition, several studies on the emission effect of RTP have revealed that, though the price system reduces load variation, environmental effects can be positive or negative depending on the nature of the peak and base load resources used to produce electricity in a region (Holland and Mansur [2008], Sioshansi [2012]). Even in terms of demand response, findings of studies by Ito [2014] and Borenstein [2009] indicate that, in the absence of advanced metering and constant knowledge of consumption, customers respond to average or expected marginal price and not marginal price. Knowledge or information feedback about electricity usage through advanced metering infrastructure can alter the previous result and increase price elasticity of demand. Empirical evidence from the study of Jessoe and Rapson [2014] suggest that feedback helps consumers to learn about the energy requirements of their household durables and reduce demand accordingly.

TOU rate is the alternative solution advocated by economists to match electricity pricing to time-varying production costs. Analyzing the effect of mandatory TOU rates on household energy consumption, Jessoe et al. [2012] find that response to the pricing scheme is consistent with the economic theory of demand, particularly among high-energy users and for peak period consumption. Even as an incentive to EV owners to charge their vehicles during off-peak hours, TOU rate is usually the suggested solution [Wolber]. Unlike RTP, TOU pricing scheme is considered simple and readily understood, a feature necessary to effectively induce customers to shift load [Jessoe et al., 2012]. Therefore, assuming TOU pricing scheme as the most feasible policy solution in the near future, in this study, a TOU rate structure is simulated to analyze the environmental effect of moving away from tiered or block pricing to a rate plan that matches time-varying production costs of electricity and the supply cycle of renewable resources in the CAISO region.

3.3 Data Description

This section describes the various datasets used for analysis and presents basic descriptive statistics and trends in the data.

3.3.1 Data on Emissions and Demand for Electricity

Considering the five year period from 2010 to 2015, the most recent period for which all the data is available, datasets from the U.S. Energy Protection Agency (EPA), Energy Information Administration (EIA), and Federal Energy Regulatory Commission (FERC) are combined to analyze the effect of residential demand for electricity on carbon dioxide (CO_2) emissions. Data on CO_2 emissions is obtained from the Continuous Emissions Monitoring System (CEMS) maintained by the EPA. CEMS contain data on emissions (in mass tons) from every fossil fuel plant with at least 25 megawatts (MW) of generating capacity.[6] Data on demand for electrical power is obtained from FERC Form 714 for the same period of time (2010-2015). Unlike data on emissions, hourly demand for electricity is reported at the level of a planning area.[7]

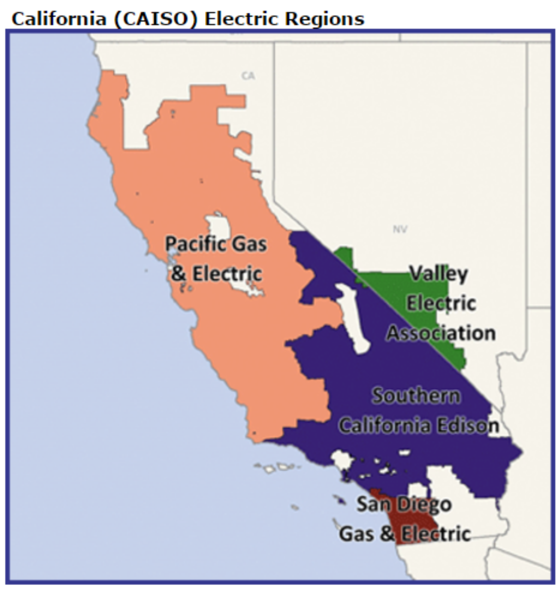
In this paper, the focus is on consumer response to TOU pricing structure and its environmental effects (CO_2 emissions) for the California ISO (CAISO) region. Therefore, data on CO_2 emissions from only the generating units located in the CAISO region are used for the purpose of the current study. Likewise, the data for load demand is from the San Diego Gas and Electric, Southern California Edison, Pacific Gas and Electric, and Valley Electric Cooperation, the planning areas under CAISO. This, in turn, implies that the estimates for marginal emissions are based on the assumption that the entire load demand in the area

[6] In addition to CO_2, CEMS data has information on SO_2 and NO_x emissions at an hourly level for the period of study.

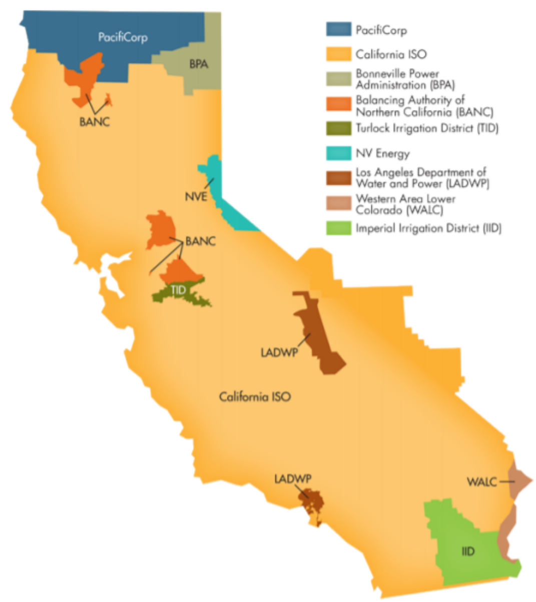
[7] Planning area is the electric system wherein an electric utility is responsible for the forecasting of system demands and has the obligation to provide the resources to serve those demands.

is satisfied by power plants located in the CAISO region. Figure 3.4 provides a general overview of the CAISO region and other balancing authorities in the state of California.

Figure 3.4: California ISO Region
Source: Federal Energy Regulatory Commission



(a) Planning Areas of CAISO Region



(b) Balancing Authorities, California (2015)

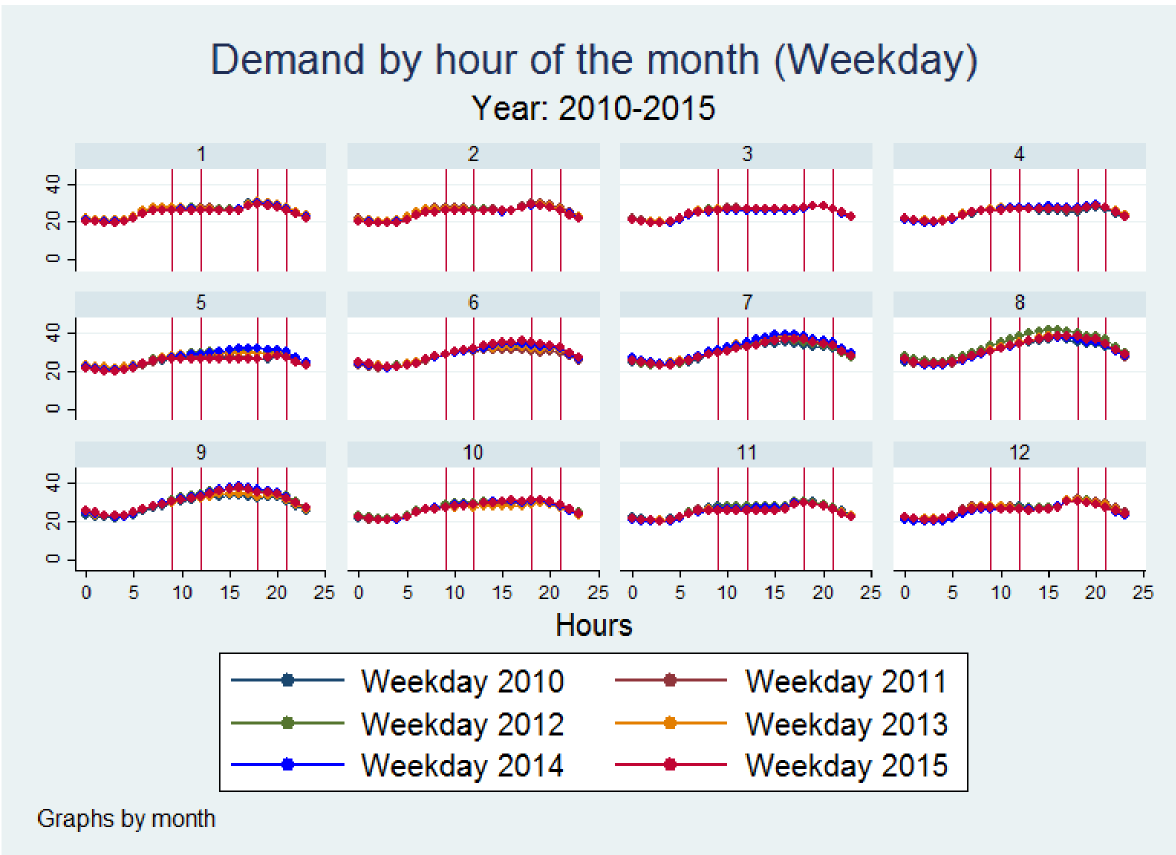
Recent literature on emissions from the power grid has emphasized the importance of studying marginal emissions at the interconnection level. Interconnections are important as they identify the entire region over which electricity is traded; changes in demand at any location could affect the generation of a marginal plant anywhere within the interconnection. Though trading is an important component of the electricity supply market, CAISO being the largest of about 38 balancing authorities[8] in the western interconnection, handling an estimated 35 percent of the electric load, the assumption that the load demand in the area is supported mostly internally is not unreasonable.[9] In spite of the shortcoming of the assumption of no interchange between CAISO and the rest of the Western Interconnection, as pointed out

[8]Balancing authority is the area operator responsible for matching generation and load, maintaining scheduled interchange with other balancing authority areas, and maintaining the frequency in real-time, of the electric power systems.

[9]80 percent of the peak summer demand in 2015 was met without any interchange.

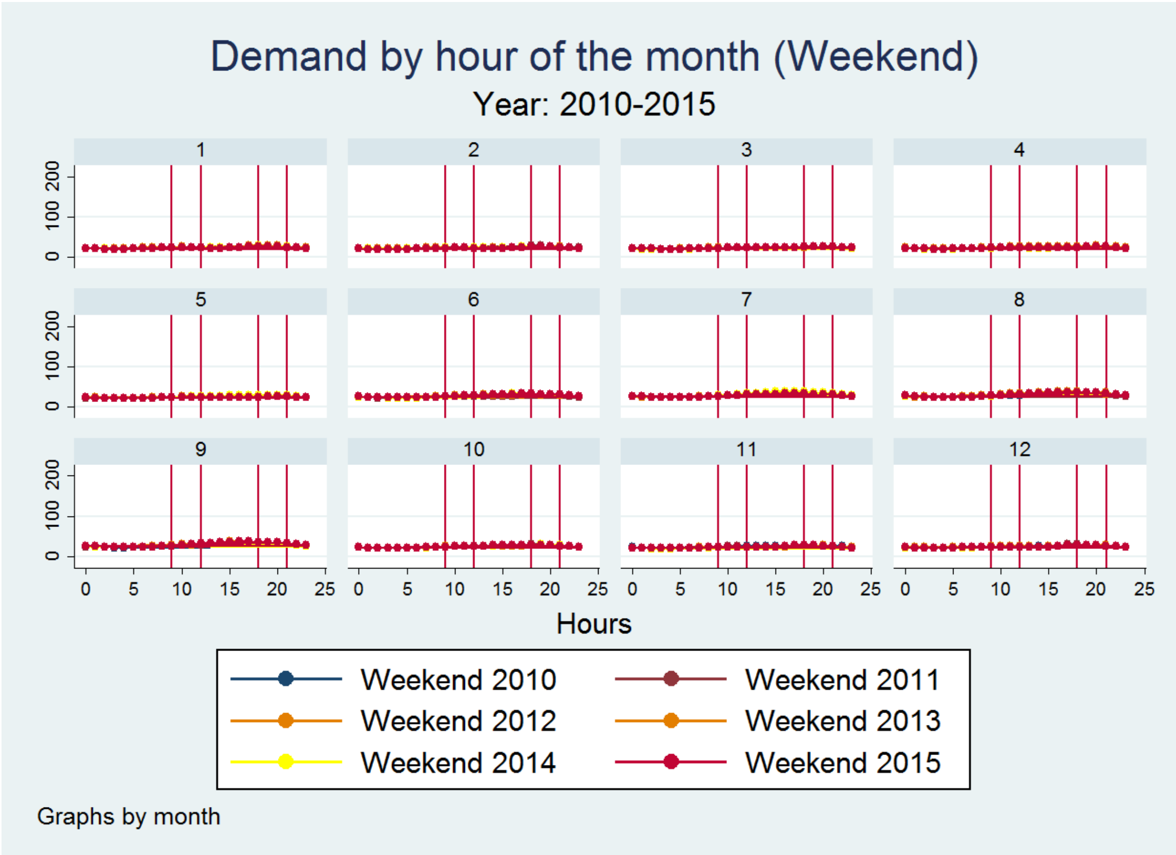
by Zivin et al. [2014], the estimates of marginal emission will offer an approximation of the environmental effect of increase in load demand due to EV charging. Figure 3.5, Figure 3.6, Figure 3.7, and Figure 3.8 offer an overview of the median load demand and emissions by the hour of the day for each month in the sample year (2010-2015) for weekdays and weekends respectively under the assumption of ‘no electricity trading’.

Figure 3.5: Demand by hour of the month in the CAISO Region (Weekday): 2010-2015



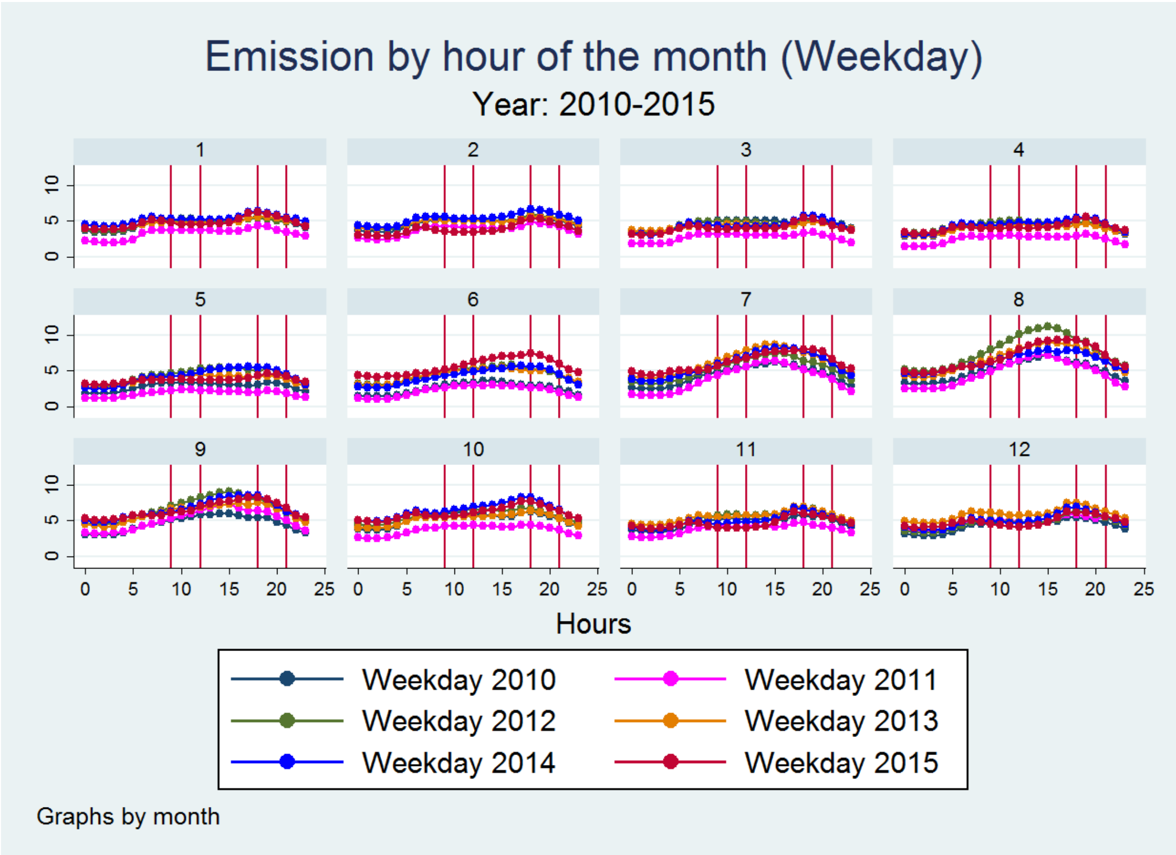
One way of incorporating electricity trading into the current model would be to use the EIA data on the hourly net interchange between CAISO and other balancing authorities and the information on regional emission factor from eGRID 2014 to calculate the amount of GHG emissions from trading. However, the data on net interchange are available from 2015. Considering the period of study here is 2010-2015, the mean interchange value can be calculated for each hour of the day from the data available (2015-2017) and used as an approximate measure of CO_2 emissions in each hour due to trading in the CAISO region.

Figure 3.6: Demand by hour of the month in the CAISO Region (Weekend): 2010-2015



An alternative approach would be to consider the extreme case of 100% import from the dirtiest possible resource and calculate the emissions due to electricity trading. The latter method would provide a measure of the bias in the marginal emission estimates obtained from the model assuming 'no trading'. Analysis with electricity trading incorporated in the regression model will be provided in future extensions of the paper.

Figure 3.7: Emission by hour of the day in the CAISO Region: 2010-2015

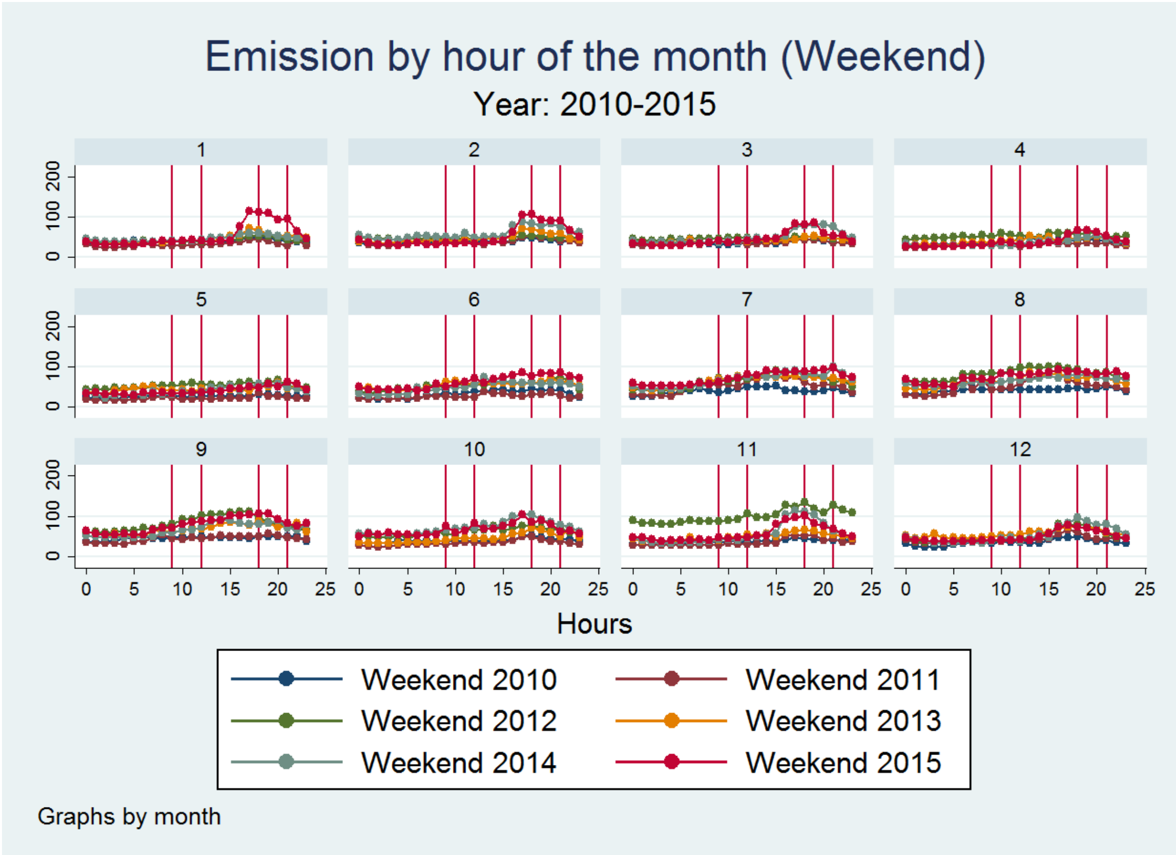


3.3.2 Data on EV Charging Behavior

In the period 2011-2013, San Diego Gas and Electric Company (SDG&E) conducted a multi-year Plug-In Electric Vehicle (PHEV) Pricing and Technology Study to get an early view of consumer response to time-varying rates for PHEV/EV charging. The primary goal of the study was to understand the potential impact of EV charging on the electric utility infrastructure as well as identify any negative effects of integrating the extra load into the grid.

Participants for the SDG&E study were chosen from the pool of customers who qualified for the EV project funded by the U.S. Department of Energy (DOE). All the participants of the rate experiment by SDG&E had the following common characteristics - owned or leased

Figure 3.8: Emission by hour of the day in the CAISO Region: 2010-2015



the all-electric Nissan LEAF car, had access to home electric panel, agreed to install a Blink home Level 2 charging unit offered by SDG&E, had dedicated home parking for the vehicle, and had the technology to set a timer to charge the vehicle (through the LEAF and their home charging unit). As participants in the EV Project, each household had received a Level 2 charging unit for home installation (approximate cost $1,499) and a DC fast charge port on the LEAF (approximate cost $700) at no cost, along with $1,200 in credit for installation of equipment. SDG&E installed a charging unit at the participant's home that provided power at 240 volts and 30-40 amps. In most cases, the $1,200 credit received from the EV project was sufficient to cover the cost of installation of the charging unit. In other cases, the customer had to pay for any installation cost above $1,200.[10]

[10]The installation cost for the charging unit ranges between $600 to $1,200 depending on the configuration of the home and electrical complexity of the installation.

The study tested three experimental TOU rates, designed to analyze consumer response to low, medium, and high price ratio between the peak and super off-peak period of electricity demand during a day. Noon to 8 p.m. was defined as the peak period, 8 p.m. to 12 a.m. and 5 a.m. to noon as the off-peak, and 12 a.m. to 5 a.m. as the super off-peak period. These TOU periods did not vary by day of week, holidays, or seasons, but the TOU rates varied between the summer (May 1- October 31) and winter (November 1-April 30) for all three groups. The low rate (EPEV-L) had an on-peak to super off-peak price ratio of approximately 2:1, the medium rate (EPEV-M) had a ratio of 4:1, and the high rate (EPEV-H) ratio was approximately 6:1. Table 3.1 gives a description of the experimental design.

SDG&E employed a randomized control trial (RCT) experimental design whereby customers who chose to be a part of the rate experiment were randomly assigned to one of the three TOU rates for the entire duration of the study. The experimental rate structure applied only to their EV charging behavior, metered separately on a dedicated 40 amp home circuit. SDG&E only examined households' home charging behavior. Participants were not given any 'bill protection' in order to maintain the integrity of the research design and measure the true impact of TOU pricing on charging behavior.

Even though this is a unique dataset, there are certain drawbacks in the experiment design, and therefore, the estimates of elasticity obtained using the data need to be interpreted accordingly. First, the respondents in the sample are early adopters of electric vehicles. While their response to pricing strategies can be expected to be representative of EV customers in the near future, the extent to which it represents the behavior of EV owners, in the long run, is uncertain. Secondly, the study did not account for household access to workplace charging. Though on average 77% of the charging events in the study period were at home location (EV Project Nissan LEAF Vehicle Summary Report for San Diego Region: July 2012-December 3013), the experiment data may not capture behavioral responses in their entirety. Keeping the above drawbacks in mind, the price elasticity estimates reported in

Table 3.1: Experimental Time-of Use (TOU) Rates

Period		SDG&E Experimental TOU Rates					
		EPEV-Low		EPEV-Medium		EPEV-High	
		$/kwh	Ratio to Super Off-Peak	$/kwh	Ratio to Super Off-Peak	$/kwh	Ratio to Super Off-Peak
Summer	Peak	0.25	1.92	0.28	4	0.36	6
	Off-peak	0.16	1.23	0.17	2.42	0.14	2.33
	Super Off-peak	0.13	-	0.07	-	0.06	-
Winter	Peak	0.17	1.31	0.23	2.87	0.32	4.57
	Off-peak	0.16	1.23	0.16	2	0.13	1.85
	Super Off-peak	0.13	-	0.08	-	0.07	-

Period		Tiered Rate ($/kwh)
Summer	Tier 1	0.14
	Tier 2	0.17
	Tier 3	0.26
	Tier 4	0.28
Winter	Tier 1	0.14
	Tier 2	0.17
	Tier 3	0.24
	Tier 4	0.26

[1] Information on experimental rates obtained from the Nexant study 'Final Evaluation for San Diego Gas & Electric's Plug-In Electric Vehicle TOU Pricing and Technology Study' (2014). The original price was rounded to two decimal places by the Nexant study.
[2] The rates represent total bundled rates that include the Utility Distribution Company (UDC) charge, the Department of Water Resources Bond Charge (DWR-BC) and Electric Energy Commodity Charge (EECC) rates.

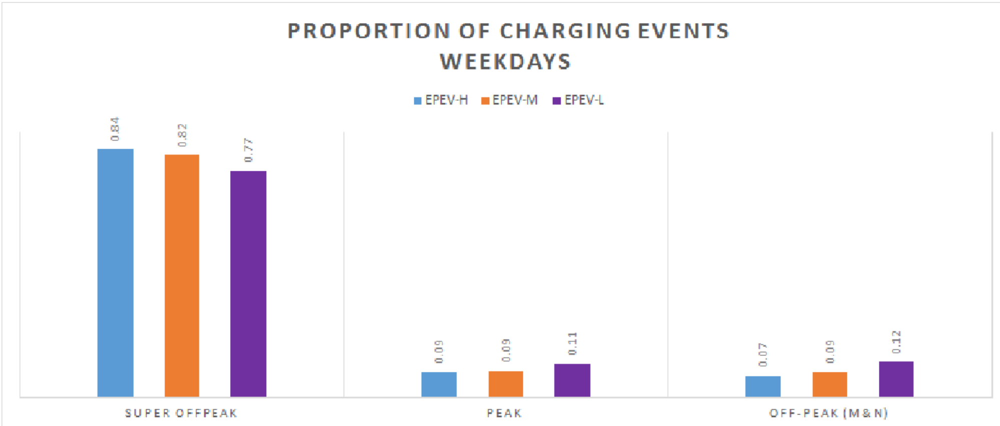
the paper can be considered a lower bound of the expected response in terms of EV charging behavior from households facing alternative TOU price structures.

Preliminary analysis of the data reveals that household charging behavior is sensitive to the price ratio between the super off-peak and peak period. During both weekdays and weekends, a higher proportion of charging events are observed during the super off-peak hours for households subjected to the EPEV-H and EPEV-M rates than those facing the EPEV-L rate (Figure 3.9).

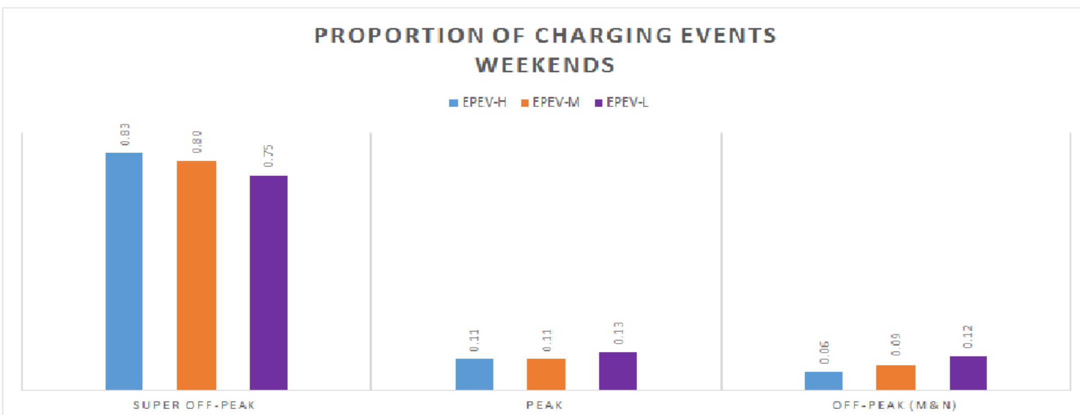
A similar pattern is observed in terms of total energy consumption by the hour of the day. Households subjected to the highest price ratio between the super off-peak and peak period have higher energy consumption during the super off-peak periods of the night compared to households facing a lower price ratio (Figure 3.10).

Additionally, a learning effect is observed in charging behavior for all households, particularly for the peak period. Figure 3.11 presents the average super off-peak and peak proportion of

Figure 3.9: Proportion of Charging Events by Time-of-Use Price Periods



(a) Weekday (Mon-Fri)



(b) Weekend (Sat & Sun)

daily EV charging events by the number of months from the beginning of the experiment. First, as observed in Figure 3.11, EPEV-L households had slightly lower levels of super off-peak charging than the other two rate groups and the difference persisted over the months. Second, an upward trend is observed in the share of super off-peak charging events in the first 2 months after which the share remains fairly stable throughout the experiment. One possible reason for this pattern is that the participants went through a learning phase related to how to use their vehicles, how the TOU rate worked in light of feedback from the monthly bill, or how to utilize the charging timer. In the case of the peak period, the number of charging events is high in the initial months, particularly for EPEV-L households but drops

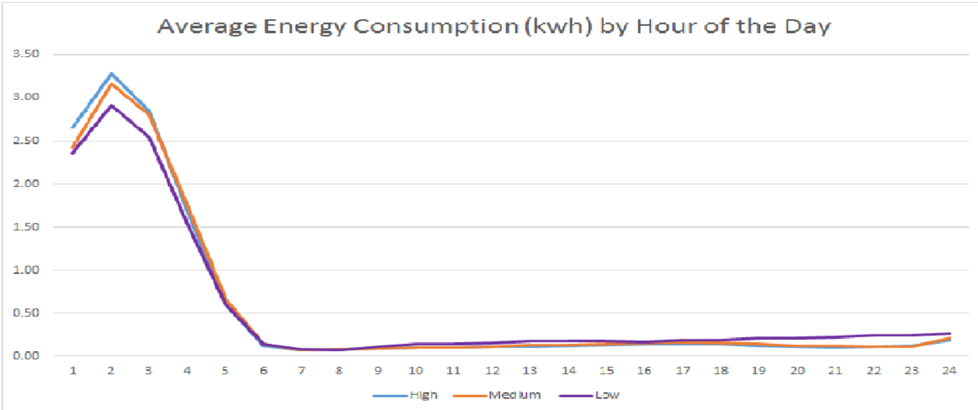


Figure 3.10: Average Energy Consumption (KWH) by TOU Rate Groups

post month 4. Finally, charging behavior is fairly stable for the EPEV-H and EPEV-M group in case of the off-peak period but not for the peak period.[11]

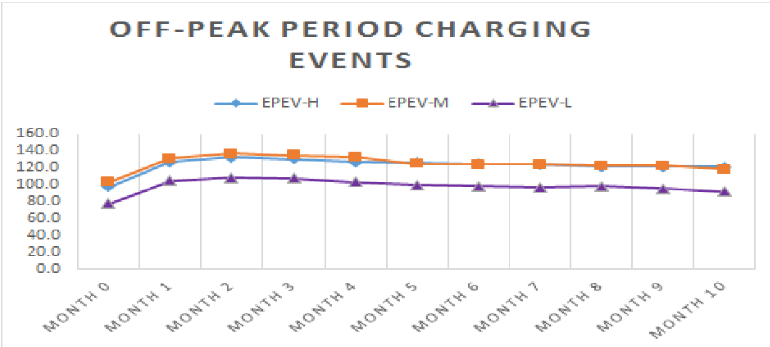
In order to formally test for difference in charging behavior among the three rate groups, a panel regression model is estimated with the monthly average proportion of peak and super off-peak charging events as dependent variables. The explanatory variables in the regression include dummy variables denoting the customers' rate group, a dummy for season, an indicator when the treatment month is among the first four months, total number of months in the experiment, and an interaction between the two.[12]

The estimated coefficients from the model provide measures of the average differences in the proportion of charging shares between households facing different rates. As expected, the EPEV-L rate induced lower super off-peak charging than EPEV-H and EPEV-M. Considering the randomized experimental design, the estimated difference in shares can be interpreted as causal. Separate models were estimated for weekdays and weekends since driving and charging behavior can differ significantly between the two. The estimates of the difference

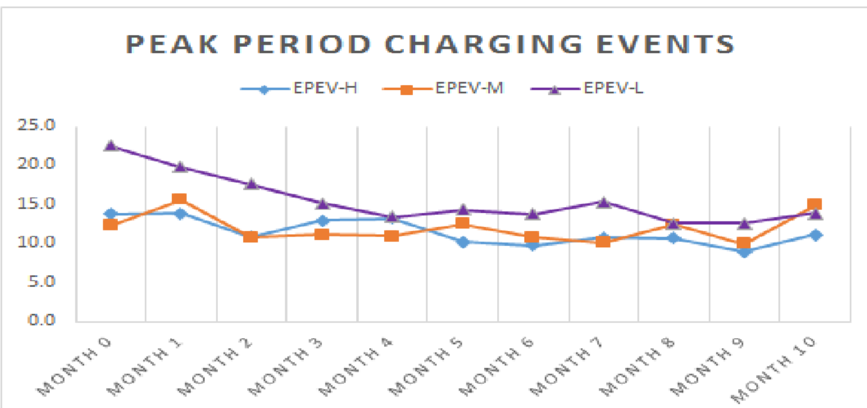
[11]Month 10 represents an average number of charging events in month 10 and beyond. For all the income groups an increase in number of charging events is observed.

[12]A panel regression model with random effects is estimated for the average proportion of peak and super off-peak charging events incorporating panel corrected standard errors to account for the fact that the observations for a given household over time are likely to be correlated.

Figure 3.11: Change in Charging Patterns by TOU Rate Group



(a) Trend of Super off-peak Charging Events



(b) Trend of Peak Charging Events

in charging behavior among the three rate groups are provided in Table 3.2

The data on hourly energy consumption by households corresponding to different rate structures are used to estimate own-price and cross-price elasticity of demand for energy to charge an electric vehicle. The elasticity estimates are subsequently used to calculate the effect of a change in electricity price structure on load demand for EV charging in the SDG&E area and therefore on emissions in the CAISO region. It is assumed that a change in load demand in the SDG&E service area will proportionately affect demand in the CAISO region and consequently the emissions in the region.

Table 3.2: Pairwise Difference in Charging shares Between Rate Groups

		EPEV-L–EPEV-H	EPEV-M–EPEV-H	EPEV-L–EPEV-M
Weekday	Peak	0.038*	0.009	0.029**
	Super Off-Peak	-0.088*	-0.02	-0.068*
Weekend	Peak	0.031*	0.02	0.011
	Super Off-Peak	-0.081*	-0.04**	-0.041

*=significant at 1% and **=significant at 5%

3.4 Estimation: Methodology and Results

3.4.1 Demand for Electricity and Emissions: CAISO Region

In this section, the effect of load demand on marginal rate of CO_2 emissions is analyzed in a framework similar to Zivin et al. [2014]. As demand for electricity changes by the time of the day, the emissions differ depending on the source of energy used to supply power to the grid. Marginal emissions also depend on the availability of resources and therefore it can differ by month of the year. For example, during the summer months, as the availability of hydropower reduces, utilities may have to use combustion turbines more regularly to meet peak demand. The model specification should account for both effects in order to get an estimate of the marginal emissions due to change in load demand. Two different model specifications are estimated here. In the first model, hourly emissions are regressed on corresponding demand in the CAISO region, controlling for the month in the sample. E_t denotes CAISO's aggregate hourly CO_2 emissions in mass tons in hour 't'.[13] The contemporaneous quantity of electricity demanded in the same hour 't' in gigawatt hours is given by d_t.

$$Model\ 1: \ E_t = \alpha + \sum_{m=1}^{12}\sum_{h=1}^{24} \beta_{h,m} * month_m * hour_h * d_t + \sum_{m=1}^{72} \gamma_m * month_m^y + \epsilon_t \quad (3.1)$$

where, t= hour (h) in day (d) of month (m) in year (y).

[13]The emission amount is scaled by 1000 for the purpose of analysis.

Equation 3.1 is estimated using ordinary least square regression with clustered standard error at the plant level. The coefficients of interest $\beta_{1,1}, \beta_{1,2}....\beta_{12,24}$ provide estimates of marginal emissions of consumption for each hour of a month in the sample for the CAISO region. γ_m estimates the fixed effect for each month of the sample. Results from regressing carbon dioxide emissions on demand in hour 'h' of month 'm' controlling for each month of the sample are given in Table 3.3.

While usually in any market quantity demanded and thereby emissions would be a function of price, in this case, d_t can be considered exogenous since households do not face the wholesale electricity prices. Therefore, the derived demand for wholesale electricity is perfectly inelastic, with minor exceptions that pose no difficulty in the analysis [Zivin et al., 2014].

Emission in time period t depends on the dispatch curve and availability of resources. It is assumed that the same resources are available during a month 'm' in sample year 'y'. However, in this model specification, the effect of demand on CO_2 emissions can vary by month of the year due to variance in the availability of resources. The dispatch curve may depend on plant closures for maintenance affecting CO_2 emissions. Anomalies in weather condition in a certain month can affect demand as well and thereby emissions.[14] Therefore, controlling for the fixed effect of the month of the year in the sample, the marginal emissions should depend only on the demand conditions in hour 'h' of month 'm'.

[14]For example, resource availability is assumed to be constant in February 2011 but it can be different in February 2012.

Figure 3.12: Marginal emissions of Carbon Dioxide (tons) in CAISO Region (Weekdays)

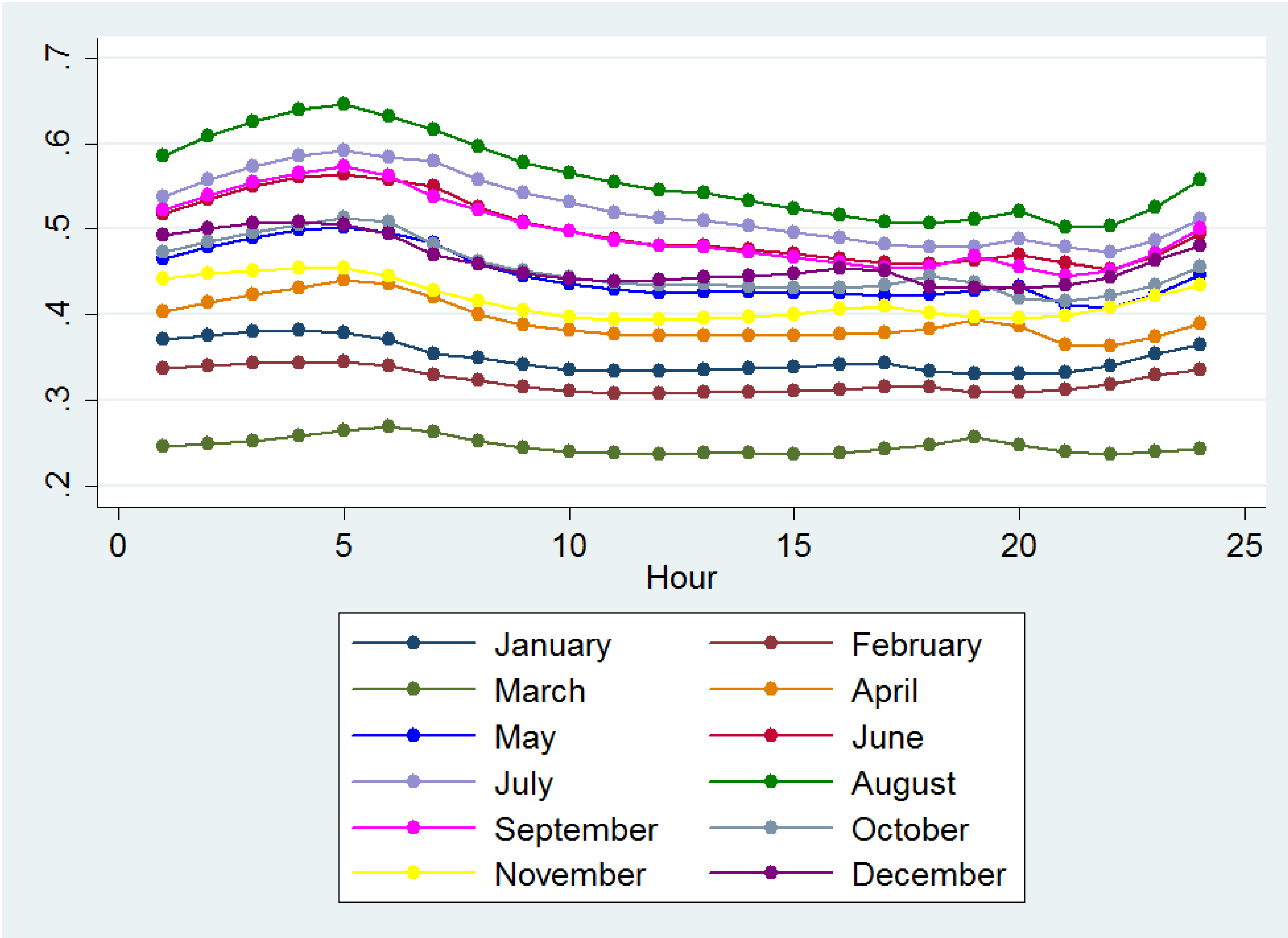


Table 3.3: Marginal Emissions of Carbon Dioxide (in tons): CAISO Region (Weekdays)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Hour												
1	0.371***	0.338***	0.246***	0.403***	0.466***	0.517***	0.538***	0.586***	0.523***	0.473***	0.442***	0.493***
2	0.376***	0.341***	0.250***	0.415***	0.479***	0.535***	0.557***	0.608***	0.540***	0.486***	0.448***	0.501***
3	0.380***	0.343***	0.253***	0.424***	0.490***	0.550***	0.573***	0.626***	0.554***	0.496***	0.452***	0.507***
4	0.382***	0.344***	0.258***	0.432***	0.500***	0.561***	0.586***	0.640***	0.566***	0.506***	0.455***	0.508***
5	0.379***	0.344***	0.265***	0.440***	0.503***	0.563***	0.591***	0.645***	0.573***	0.513***	0.455***	0.506***
6	0.370***	0.340***	0.270***	0.436***	0.496***	0.558***	0.583***	0.631***	0.562***	0.509***	0.445***	0.494***
7	0.354***	0.330***	0.263***	0.420***	0.484***	0.550***	0.579***	0.616***	0.538***	0.483***	0.429***	0.470***
8	0.349***	0.324***	0.253***	0.401***	0.460***	0.525***	0.559***	0.597***	0.522***	0.463***	0.416***	0.459***
9	0.341***	0.316***	0.245***	0.388***	0.445***	0.508***	0.542***	0.577***	0.507***	0.452***	0.405***	0.449***
10	0.336***	0.311***	0.241***	0.381***	0.437***	0.497***	0.531***	0.565***	0.497***	0.444***	0.397***	0.442***
11	0.334***	0.308***	0.238***	0.377***	0.429***	0.488***	0.520***	0.554***	0.488***	0.438***	0.394***	0.440***
12	0.335***	0.308***	0.238***	0.375***	0.425***	0.481***	0.513***	0.546***	0.481***	0.435***	0.394***	0.441***
13	0.336***	0.309***	0.238***	0.376***	0.427***	0.481***	0.510***	0.542***	0.479***	0.436***	0.396***	0.443***
14	0.337***	0.310***	0.238***	0.375***	0.426***	0.476***	0.504***	0.534***	0.473***	0.433***	0.397***	0.445***
15	0.340***	0.311***	0.238***	0.376***	0.425***	0.471***	0.497***	0.524***	0.467***	0.432***	0.400***	0.449***
16	0.342***	0.313***	0.239***	0.377***	0.425***	0.465***	0.490***	0.516***	0.461***	0.431***	0.406***	0.454***
17	0.343***	0.316***	0.243***	0.379***	0.423***	0.460***	0.482***	0.508***	0.454***	0.434***	0.410***	0.452***
18	0.334***	0.315***	0.248***	0.384***	0.423***	0.460***	0.479***	0.507***	0.456***	0.445***	0.402***	0.433***
19	0.331***	0.310***	0.257***	0.394***	0.429***	0.463***	0.480***	0.512***	0.468***	0.437***	0.398***	0.431***
20	0.331***	0.310***	0.247***	0.386***	0.433***	0.470***	0.488***	0.521***	0.456***	0.418***	0.397***	0.432***
21	0.333***	0.312***	0.240***	0.364***	0.411***	0.460***	0.479***	0.502***	0.445***	0.416***	0.400***	0.435***
22	0.340***	0.319***	0.238***	0.364***	0.409***	0.452***	0.473***	0.505***	0.452***	0.422***	0.408***	0.444***
23	0.354***	0.330***	0.240***	0.374***	0.424***	0.468***	0.487***	0.526***	0.472***	0.435***	0.422***	0.463***
24	0.365***	0.336***	0.243***	0.390***	0.447***	0.494***	0.512***	0.558***	0.500***	0.456***	0.435***	0.481***

The coefficients in Table 3.3 relates the fractional increase in CO_2 emissions to a given fractional increase in load demand. Firstly, as mentioned above, since power plants with different emission rates are dispatched at different times of the day and year, the coefficients vary by hour of the day and month of the year. Second, marginal emissions are positive for all hours indicating that the base load is a fossil fuel plant.[15] If additional demand is catered to by fossil fuel plants, marginal emissions are higher compared to the case when renewable resources are used to meet the demand.

As evident from both Figure 3.12 and Table 3.3, marginal emissions are higher in the early hours of the morning when base load capacities are turned on to meet the morning demand for power and in the early hours of the evening when supply from renewable resources are lower and the natural gas turbines are ramped up to meet peak demand in the evening. The other thing to note is that marginal emissions are higher between June and September with August being the month with highest marginal emissions. On the other hand, March has the lowest marginal emissions.

Utility companies like SDG&E attempting to introduce TOU rates divide up the demand for electricity into 3 or 4 periods: Peak, off-peak (morning), off-peak (evening) and super off-peak. The dispatch curve is different in each period and therefore emissions. The following model specification (3.2) aims to capture the effect of a change in demand in period 'p' on emissions. Using the definition of TOU periods of the Multi-year Plug-In Electric Vehicle (PHEV) Pricing and Technology Study done by SDG&E, a second model is estimated where each day is divided into 3 periods: 1 a. m. to 5 a. m. (super off-peak) as period 1, 5 a. m. to noon (off-peak morning) and 8 p. m. to midnight (off-peak evening) as period 2, and noon-8 p. m. (peak) as period 3. Aggregating to the level of period 'p' in month 'm', CO_2 emissions in period 'p' is regressed on the contemporaneous load demand controlling for month fixed effects. Here, E_p denotes CAISO's aggregate CO_2 emissions in mass tons in period 'p'. The

[15] Natural gas plants form the base load capacity in California. Though emissions are lower than coal plants it is not zero.

contemporaneous quantity of electricity demanded in the same period ‘p’ in gigawatt hours is given by d_p.

$$Model\ 2: \ E_p = \alpha + \sum_{p=1}^{4}\sum_{m=1}^{12} \beta_{p,m} * period_p * month_m * d_p + \sum_{m=1}^{72} \gamma_m month_m^y + \epsilon_p \quad (3.2)$$

Here p= period (p) in a day (d) of a month (m) in a year (y).

Results from regressing CO_2 emissions on demand in period ‘p’ controlling for each month ‘m’ in the sample are given in Table 3.4. The coefficient of interest $\beta_{p,m}$ gives the marginal effect of demand on carbon dioxide emissions in period ‘p’ of month ‘m’. The model controls for fixed effects of each month of the sample. As in the earlier model, the fixed effects controls for resource availability in month ‘m’ of year ‘y’ due to plant closures or maintenance and any weather anomaly that may affect demand. Therefore, the model allows dispatch curves to differ across months but it is assumed that it is same for period ‘p’ in a particular month ‘m’ in the sample (2010-2015).

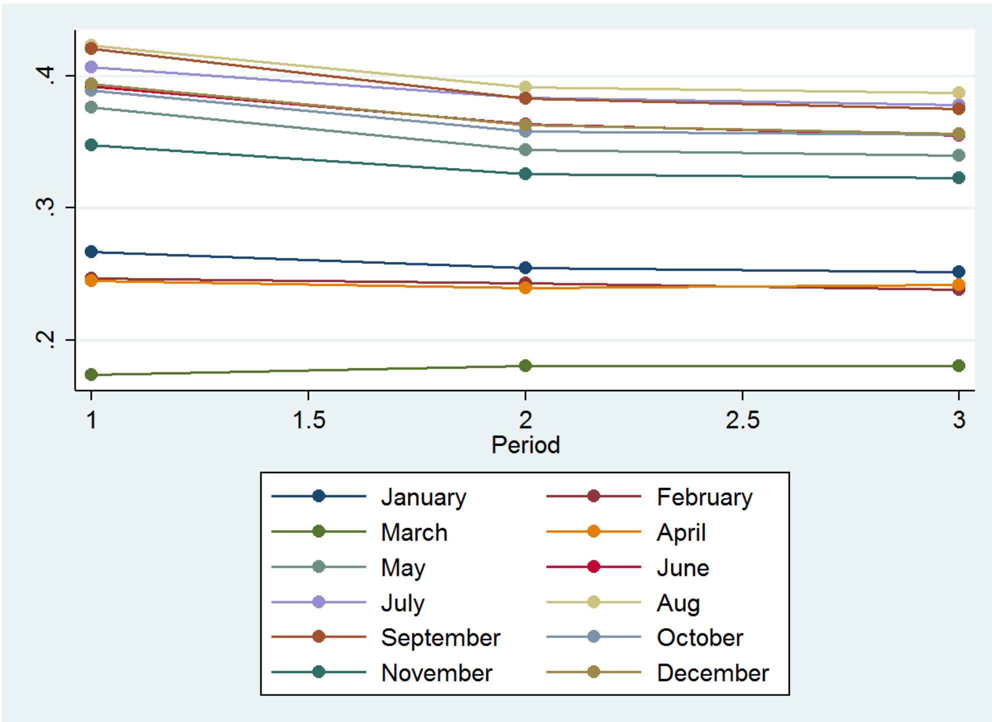
Table 3.4: Marginal Emissions of Carbon Dioxide (in tons): Time-of Use Periods by Month in CAISO Region

	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Weekday	Super Off-Peak	0.267	0.247	0.174	0.245	0.376	0.392	0.407	0.423	0.421	0.389	0.348	0.394
	Off-Peak	0.255	0.243	0.180	0.240	0.344	0.364	0.383	0.392	0.383	0.358	0.326	0.363
	Peak	0.252	0.238	0.181	0.242	0.340	0.355	0.378	0.387	0.375	0.355	0.323	0.356
All Days	Super Off-Peak	0.295	0.282	0.211	0.301	0.361	0.384	0.376	0.410	0.401	0.379	0.363	0.389
	Off-Peak	0.278	0.272	0.210	0.285	0.335	0.361	0.362	0.384	0.371	0.352	0.339	0.360
	Peak	0.273	0.266	0.210	0.286	0.331	0.353	0.359	0.380	0.365	0.350	0.335	0.353

[1] The emission amount in lbs was scaled by a factor of 1000 in the regression model for the purpose of analysis.

Marginal emissions during the super off-peak periods are higher than marginal emissions during the peak period. However, as per the definition of TOU periods in the SDG&E study, the peak period includes both the hours when the supply of solar energy is maximum in the CAISO region as well as the hours when the supply of solar energy diminishes and gas turbines are dispatched to meet the peak demand of the evening. This fact can potentially dampen the estimated effect of demand on marginal emission during the peak hours of the

Figure 3.13: Marginal emissions of Carbon dioxide (tons) in 3 TOU periods of the month (Weekdays)



day. To account for the increasing supply of solar energy in the region, SDG&E updated the definition of the super off-peak, off-peak (morning), peak period, and off-peak (evening) to 12 a. m. - 6 a. m., 6 a. m. - 3 p. m., 3 p. m. - 9 p. m., and 9 p. m. - midnight respectively in their proposal to the California Public Utility Commission to move from tier to TOU rates for all households. A third model is estimated with the proposed time periods and the results are provided in the appendix (Table C.1 and Figure C.1).

Since the experiment with EV owners was done following the 3 periods defined in Model 2, all further analysis in the paper would correspond to the same definition of TOU periods.

3.4.2 Price Elasticity of Electricity Demand for EV Charging

Measures of price elasticities are required to analyze the environmental impact of EV charging under alternative TOU rates. The elasticity of demand is estimated using the longitudinal data on EV charging behavior collected by SDG&E for their multi-year Plug-In Electric Vehicle (PHEV) Pricing and Technology Study. The elasticity estimates are then used to calculate the change in demand in response to different TOU rates in the SDG&E area and consequently the environmental impact in the CAISO region. As mentioned before, the underlying assumption is that changes in demand in the SDG&E area due to EV charging would proportionately affect demand and emissions in the CAISO region.

Own- and cross- price elasticity of electricity demand for EV charging is estimated using the Quadratic Almost Ideal Demand System (QUAIDS) developed by Banks et al. [1997], an extension of the Almost Ideal Demand System (AIDS) proposed by Deaton and Muellbauer [1980a].

In the standard utility maximization problem, a consumer makes budget allocation decisions on a large number of goods with different relative prices. The solution to this problem gives the amount demanded of each good as a function of its price, prices of other goods, and the consumer's income. However, as the number of commodities in the decision bundle increase, the consumer's allocation problem becomes complex to model empirically. The AIDS/QUAIDS framework solves the allocation problem based on the assumption of weak separability of consumer preferences. If preferences are weakly separable, then commodities can be partitioned into groups so that preferences within a particular group is independent of consumption in other groups. In other words, an individual utility function can be defined for each commodity group, such that the sum of all the group utilities gives the total utility. Based on the Price-Independent Generalized Logarithmic (PIGLOG) preference structure, the AIDS model assumes budget shares or expenditure allocations to be a linear function of log total expenditure.[16] However, as some empirical Engel curve studies have indicated, the linear functional form may not provide an accurate picture of consumer behavior and addi-

[16]The PIGLOG class of preferences are represented via the cost or expenditure function which defines the minimum expenditure necessary to attain a specific utility level at given prices. This class of preference permit representation of market demand as if they were outcome of decisions by a rational representative consumer Deaton and Muellbauer [1980a].

tional terms in total expenditure are required for some, if not all expenditure share equations (Banks et al. [1997], Bopape and Myers [2007]). The QUAIDS model proposed by Banks et al. [1997] generalizes the AIDS model allowing for nonlinearities in total expenditure. This allows goods to be classified as normal or inferior goods depending on the point in the expenditure spectrum. The AIDS/QUAIDS model has mainly found application in the literature on consumer welfare analysis related to food expenditure and the effect of taxes on consumption, labor supply, and household welfare [Gahvari and Tsang, 2011].

In the present application, assuming a two-stage budgeting process and weak separability of demand for electricity for EV charging implies that, in the first stage households allocate total expenditure or a particular budget for vehicle charging and in the second stage they decide the amount they want to spend on charging in each TOU period. Since households in the experiment were billed separately for their EV charging behavior, it is reasonable to treat expenditure on vehicle charging as a separate commodity group. Also, as households are expected to make budget allocations on a monthly basis, the daily expenditure data on EV charging is aggregated to the month level. Own- and cross-price elasticity for each TOU period is calculated from the estimates of the QUAIDS model.

The QUAIDS model of Banks et al. [1997] is based on the indirect utility function given by (3.3)

$$ln\ V(p,m) = \left[\frac{(\text{ln m} - \text{ln a(P)})}{b(P)}^{-1} + \lambda(P) \right]^{-1} \tag{3.3}$$

where $ln\ a(P)$ is a transcendental logarithmic function, b(P) is the Cobb-Douglas price aggregator, and $\lambda(P)$ is used to define the quadratic form of the utility function.

$$ln\ a(P) = \alpha_0 + \sum_{i=1}^{3} \alpha_i * ln\ p_i + (1/2) * \sum_{i=1}^{3} \sum_{j=1}^{3} \gamma_{ij} * ln\ p_i * ln\ p_j \tag{3.4}$$

$$b(P) = \prod_{i=1}^{3} p_i^{\beta_i} \tag{3.5}$$

$$\lambda(P) = \sum_{i=1}^{3} \lambda_i * ln\ p_i \tag{3.6}$$

Here, p_i is the price of electricity (per kWh) in period *i,j=1,2,3* of a day within the commodity group 'EV charging' for which budget 'm' is allocated in the first of the two-stage budgeting process. Here, *i,j=1,2,3* represents the peak, off-peak, and super off-peak periods of the day respectively.

$\alpha_i,\ \beta_i,\ \gamma_{ij},\ and\ \lambda_i$ are the parameters to be estimated. Theoretically, it is possible to estimate the value of α_0, but it is difficult in practice. Therefore, according to the rule of thumb followed by Deaton and Muellbauer [1980b] and Banks et al. [1997], α_0 is set slightly less than the lowest value of $\ln m$ observed in the data. Additivity, homogeneity, and Slutsky symmetry impose the following restrictions on the parameters:

$$\sum_{i=1}^{3} \alpha_i = 1,\ \sum_{i=1}^{3} \beta_i = 0,\ \sum_{i=1}^{3} \gamma_{ij} = 0,\ \sum_{i=1}^{3} \lambda_i = 0,\ and\ \gamma_{ij} = \gamma_{ji} \tag{3.7}$$

If q_i is the quantity of electricity consumed in period 'i' by household 'h' during a month, the expenditure share for period 'i' is defined as $w_i = (p_i * q_i)/m$. Applying Roy's identity to (3.3), the budget or expenditure share of each period 'i' as a function of prices and utility is given by (3.8)

$$w_i = \alpha_i + \sum_{i=1}^{3} \gamma_{ij} * ln\ p_j + \beta_i * ln\left[\frac{\mathrm{m}}{a(P)}\right] + \frac{\lambda_{\mathrm{i}}}{b(P)} * \left[ln\frac{\mathrm{m}}{a(P)}\right]^2 \tag{3.8}$$

For this study, the empirical specification of the QUAIDS model is extended to accommodate the panel structure of the data. In other words, the share equation for each household 'h', in period 'i', of treatment month 't' is

$$w_{it}^{h} = \alpha_i + \sum_{i=1}^{3} \gamma_{ij} * ln\ p_{jt}^{h} + \beta_i * ln\left[\frac{\mathrm{m^h}}{a(P_t^h)}\right] + \frac{\lambda_{\mathrm{i}}}{b(P_t^h)} * \left[ln\frac{\mathrm{m^h}}{a(P_t^h)}\right]^2 \tag{3.9}$$

$ln\ a(P_t^h)$ and $b(P_t^h)$ is an extension of equation (3.4) and (3.5) accounting for the panel structure of the data.

Households tend to have varying preference structures and the expenditure share in each period may depend not only on the price of electricity in each period but also on the vehicle miles traveled using the EV, the driving schedule of the household, access to alternative charging sources (like workplace charging), and other demographic characteristics that can affect price sensitivity. The empirical specification should ideally account for these sources of heterogeneity in preferences. However, as none of this information is available in the data, the model estimated below does not account for these sources of heterogeneity and therefore the estimates may be biased. The empirical specification, however, does include the month of treatment as a dummy variable to control for structural changes in consumers' preferences and other aggregate learning effects that may influence expenditure. Also, we include the season (summer/winter) as a dummy variable to account for any seasonal difference in expenditure behavior.

The nonlinear QUAIDS model can be estimated using the stata program written by Poi [2012] to model a four-equation demand system with demographic variables. The QUAIDS program assumes an additive zero-mean error term (multivariate normal) associated with each of the expenditure share equations. The parameters are then estimated by iterated feasible generalized nonlinear least squares estimation.[17] To avoid a singular error-covariance matrix, the QUAIDS program automatically drops the last equation from the estimation routine. The program imposes the required additivity, homogeneity, and Slutsky restrictions on the parameters. In the QUAIDS program developed by Poi [2012], socio-demographic factors are included using the scaling technique introduced by Ray [1983] whereby the household expenditure function in each share equation 'i' is scaled by a factor that is a function of household demographics.[18] Estimation results obtained from using the QUAIDS program in stata is given in Table C.2 in the appendix.

The biggest drawback of the canned QUAIDs program in Stata by Poi [2012] is that missing observations are dropped from the estimation process. In other words, the estimates are based only on positive share data. This may give rise to inconsistent estimates if there are many observations with zero household expenditure on a particular good or charging period in this case. One way of dealing with the zero expenditure problem in the estimation of budget share models is to aggregate the data to a level where it is consistent with the research question such that there are fewer instances of zeros and therefore the bias introduced by estimating the model only on observation with positive expenditure is reduced. In the current scenario, even after integrating the data to the monthly level such that it is consistent with the theory of two-stage budgeting, there are 118 (1.2%) instances of zero expenditure in the super off-peak period, 3,195 (34%) in the off-peak, and 4,422 (48%) cases of zero shares in the peak period out of 9,237 observations. In this case, demand for electricity can be treated as censored in each period such that estimation of the Tobit regression model can give the elasticity estimates. However, the underlying assumption of the Tobit model for observed zero expenditures is that the market price for a given commodity exceeds the household's reservation price, leaving the household at a corner solution and censoring the

[17] The iterated feasible generalized nonlinear least square estimator is equivalent to the multivariate normal maximum likelihood estimator for the seemingly unrelated regression class of models

[18] Further details on the model specification and scaling factors used in the QUAIDS program is available in Stata Journal Volume 3, 2012

expenditure distribution at the point of nonconsumption. This may not be the case with electricity consumption for vehicle charging. A more likely reason for non-consumption in the current scenario is infrequency of vehicle charging, which occurs when charging events are not observed due to the short span of the survey period. The p-tobit model by Deaton and Irish [1984] or the 'double-hurdle' model of Cragg [1971] are possible ways of dealing with this problem, though the latter model is more relevant in the case of corner solution.

An alternative method to account for zero expenditure shares involves a two-step estimation procedure for a system of equations with limited development variables introduced by Shonkwiler and Yen [1999]. Shonkwiler and Yen [1999] extended the Amemiya [1974] Type II Tobit model.[19] Their model contains as the first step a single equation probit model used to predict the probability of consumption for each good in the system. This is then multiplied by the expectation of demand for the respective good conditional on positive consumption to generate the unconditional censored demand equations. The demand system is subsequently estimated in the second stage by either maximum likelihood or seemingly unrelated regression.

The following system of equations are estimated in the two stages of the procedure:

$$y_{it}^{h*} = f(X_{it}^{h}, \beta_i) + \epsilon_{it}^{h} \; and \; d_{it}^{h*} = z_{ti}^{h'} \alpha_i + \nu_{it}^{h} \tag{3.10}$$

$$\begin{aligned} d_{it}^{h} &= 1 \; if \; d_{it}^{h*} > 0 \\ &\quad 0 \; if \; d_{it}^{h*} < 0 \end{aligned} \tag{3.11}$$

[19] In the Type II Tobit model the effect of the Xs on the probability that an observation is censored and the effect on the conditional mean of the non-censored observations are not the same. X can have an effect on the decision to participate (probit part) and a different effect on the amount of consumption (truncated regression). It is also known as the Heckman Selection Model.

$$y_{it}^h = d_{it}^h * y_{it}^{h*} \tag{3.12}$$

(h=1,2,...n households, t=1,2,3... m months of treatment, and i=1,2,3 periods)

y_{it}^h and d_{it}^h are observed dependent variables in the two stages of the procedure representing the share of expenditure on charging in period 'i' and the event of charging the vehicle in period 'i' respectively. y_{it}^{h*} and d_{it}^{h*} are the corresponding latent variables while X_{it}^h and z_{it}^h are vectors of exogenous variables.

In the first stage, a probit model is estimated for each period 'i' to obtain the estimates of $\hat{\alpha}_i$, $\phi(z_{it}^{h'}\hat{\alpha}_i)$, and $\Phi(z_{it}^{h'}\hat{\alpha}_i)$. In the second stage, the share model is estimated using non-linear seemingly unrelated regression methods to recover the β and δ parameters from

$$w_{it}^h = \Phi(z_{it}^{h'}\hat{\alpha}_i)\left(\alpha_i + \sum_{i=1}^{3}\gamma_{ij} * ln\, p_{jt}^h + \beta_i * ln\left[\frac{\mathrm{m^h}}{a(P_t^h)}\right] + \frac{\lambda_\mathrm{i}}{b(P_t^h)} * \left[ln\frac{\mathrm{m^h}}{a(P_t^h)}\right]^2\right) + \delta_i * \phi(z_{it}^{h'}\hat{\alpha}_i) + \xi_{ti}^h \tag{3.13}$$

In both steps of the two-step procedure, all observations of the sample are applied. However, as the right-hand side of the system does not add up to one in the second stage, the adding-up conditions specified in equation (3.7) cannot be imposed. Therefore, the system must be estimated based on the full n-vector (Yen et al. [2002], Ecker et al. [2008], Nigussie and Shahidur [2012]).

Expenditure and price elasticities are estimated by differentiating equation (3.13) with respect to lnm and lnp_j, such that

$$\mu_i = \frac{\partial w_{it}^h}{\partial lnm} = \Phi(z_{it}^{h'}\hat{\alpha}_i)\left(\beta_i + \frac{2\lambda_i}{b(P)} * ln\frac{m}{a(P)}\right) \tag{3.14}$$

and

$$\mu_{ij} = \frac{\partial w_{it}^h}{\partial lnp_j} = \Phi(z_{it}^{h'}\hat{\alpha}_i)\left(\gamma_{ij} - \mu_i(\alpha_j + \sum_{k=1}^{3}\gamma_{jk} * lnp_k) - \frac{\lambda_i\beta_j}{b(P)} * \left[ln\frac{m}{a(P)}\right]^2\right) \tag{3.15}$$

where p_k is a price index calculated as the arithmetic mean of prices for all i periods in the system. The conditional expenditure elasticities are then obtained by calculating $e_i = \left(\frac{\mu_i}{w_{it}^h} + 1\right)$. The conditional Marshallian (uncompensated) price elasticities are derived as $e_{ij}^u = \left(\frac{\mu_{ij}}{w_{it}^h} - \delta_{ij}\right)$, where δ_{ij} is the Kroneckar delta equating to one when $i \neq j$, zero otherwise. Using the Slutsky equation, the conditional Hicksian (compensated) price elasticities are given by $e_{ij}^c = \left(\frac{\mu_{ij}}{w_{it}^h} + e_i * w_{jt}^h\right)$. All elasticities are computed at sample means.

The system is estimated using a modified version of the Poi [2008] model written in Stata taking into account the two-stage correction method for zero consumption expenditure. Table 3.5 provides the elasticity measures calculated from QUAIDS model estimated using seemingly unrelated regression methods. It is important to note that the two steps in the correction procedure have been estimated separately. This implies that the elasticity estimates are consistent but the standard errors are not correct. One way of gaining efficiency and correcting the standard errors would be to combine the first-step (probit) and the second-step (system) estimations by jointly estimating each block using the maximum likelihood procedure within one optimization algorithm [Shonkwiler and Yen, 1999]. Intuitively, all own-price elasticities should be negative, while cross-price elasticities can be positive or negative depending on whether two goods are substitutes or complement respectively. Pos-

Table 3.5: Uncompensated Price Elasticity for EV Charging in the SDG&E Area (weekdays)

Summer				
	Period	Super Off-Peak	Off-Peak	Peak
Weekdays	Super Off-Peak	-0.325	-0.079	0.047
	Off-Peak	-1.936	-6.837	-6.422
	Peak	-1.131	-4.638	-4.789
Winter				
	Period	Super Off-Peak	Off-Peak	Peak
Weekdays	Super Off-Peak	-0.302	-0.166	-0.113
	Off-Peak	-2.566	-5.877	-4.344
	Peak	-2.620	-4.558	-4.678
Both Seasons				
	Period	Super Off-Peak	Off-Peak	Peak
Weekdays	Super Off-Peak	-0.353	0.177	0.297
	Off-Peak	-1.436	-0.724	-0.252
	Peak	1.372	-0.382	-0.873

[1] The elasticities are based on the output of the modified nlsur model developed by [Poi, 2008]

[2] Row 'i', column 'j' of each elasticity matrix represents the percentage change in the quantity of good 'i' consumed for a 1% change in the price of good 'j'.

[3] The $\alpha_0 = 0.7$ in the model.

itive cross-price elasticities indicate that as the price of electricity increases in one period, the demand increases in another time period. Conversely, negative cross-price elasticities indicate that the goods are complements or in other words as the price of electricity increases during one time period, the demand for electricity decreases in the other period. Consistent with economic intuition, all own-price elasticity measures have a negative sign. The own-price elasticity of the peak and the off-peak period is higher than that of the super off-peak period. The lower own-price elasticity estimate for the latter is likely due to the convenience of charging in that period, usage of timers, and the possibility of long charging event that fits within the super off-peak time period.

The cross-price elasticities are positive for peak and super off-peak period of charging while it is negative for the peak and off-peak period in the summer. The latter result is potentially driven by the fact that households mostly charge their vehicles in the super off-peak period and use peak and off-peak period charging only if necessary. Moreover, both the off-peak periods (morning and evening) as defined in the study were not long enough to complete a charging event. During both the times of the day, it is likely that the vehicle needs to be plugged-in for a few hours into the peak period making the two periods complimentary. Finally, uncompensated price elasticity is usually smaller during the winter months than summer. A potential reason driving the result can be the lower use of air condition in non-summer months and therefore lower need for vehicle charging.

This data has been previously analyzed by Nexant using an expenditure share model. The elasticity measures estimated here are higher than those reported by the Nexant study where own-price elasticities ranged between 0.3-0.5. Unlike the Nexant study, the above model accounts for zero expenditure by households on vehicle charging during a certain TOU period.[20]

3.5 Alternative Time-of-Use Price Scenarios

In California, residential electricity consumption is currently priced using a tiered or block pricing structure. In the past few years as the share of EVs have progressed, Pacific Gas & Electric, Southern California Edison, and SDG&E have introduced the option of TOU rates for EV owners to incentivize vehicle charging during super off-peak hours of the night. To encourage overall economic and environmental efficiency in energy consumption, the California Public Utility Commission (CPUC) has mandated all three utilities to switch from block pricing to TOU rate plans at the household level from 2018.

In comparison to the tiered pricing structure, though TOU rate can incentivize more efficient use of resources, reducing the environmental cost of electricity usage as well as the economic

[20]In the report there was no information about the possibility of zero expenditure in the data and the method used to deal with the issue

cost for both utilities and consumers, it needs careful implementation. At present, the market share of EVs in California is 2.7%. If the target of 15% share of EVs in new vehicle sales is met by 2025, the current TOU structure can potentially create a new peak period of load demand in areas with high EV penetration as vehicle owners start charging as soon as the rate drops after the usual evening peak hours. The environmental effect of this phenomenon would depend on the marginal plant and the energy source used to meet the demand. If the marginal plant is powered by the wind or hydro power marginal emissions will be low, but emissions will be high if it is a natural gas plant. The extent to which the problem of a 'new peak' in residential consumption of electricity may rise will also depend on the availability of workplace charging and the future network of public charging stations. Moreover, TOU rates are only effective to the extent they are designed to incentivize charging when electricity generation is less costly and there is the availability of clean energy resources to meet the additional load demand. If rates are structured poorly, or fail to keep up with changing electricity generation cost profiles (such as increased solar generation causing mid-day electricity costs to drop in California), they may be counter-productive to efficient EV charging.[21]

Even though the model estimated in the current paper cannot take into account the effect of increase in EV market share on emissions or the availability of workplace charging, given the current share of EVs, analyzing the effect of alternative price structures on EV charging behavior will allow us to understand if there are environmental benefits of moving from tiered electricity pricing to TOU rates. Additionally, from the viewpoint of the design of the rate structure, it is important to understand the environmental effects of aligning the TOU periods with the supply cycle of renewable resources. It can be hypothesized that daytime charging can reduce the intensity of electricity demand for vehicle charging during super off-peak and off-peak hours while using the often curtailed solar energy in California. In other words, workplace charging encouraged by appropriately designed TOU rates

[21] http://www.synapse-energy.com/sites/default/files/A-Plug-for-Effective-EV-Rates-S66-020.pdf

can generate environmental benefits in comparison to the current system of concentrating charging behavior only to the super off-peak hours of the night. As mentioned earlier, the environmental effect of daytime charging versus vehicle charging during super off-peak hours of the night can vary by season. In other words, during summer months when the availability of hydropower is low and average residential demand for energy is high due to cooling needs, additional demand for vehicle charging might cause negative environmental effects along with overload risks. On the other hand, daytime charging can be beneficial during the winter months in California when average demand is lower compared to summer months and there is abundant solar energy.

In order to understand the environmental consequences of EV charging under TOU rate structure and the effect of implementing seasonal variation in the rates, marginal emission, and total emission cost are analyzed under the following scenario.

Case (I): Shift from Tiered Pricing to TOU rates: EPEV-H rate during the summer months and EPEV-L rate in the winter.

SDG&E at present has the three tier pricing structure and depending on the amount of energy consumption, households are assigned to one of the tiers. Once households are in a particular tier, the rate of electricity consumption is same regardless of the time of the day. In other words, two households will pay the same electricity bill even though one may consume more during the peak hours while the other has higher consumption in the off-peak period of the day. In general, larger households fall in the third tier facing a price of $0.26/ kWh during the summer months and $0.24/ kWh in the winter. Assuming households with EVs are comparatively big with multiple vehicles, Tier 3 rate is chosen as the base case pricing scenario.

In the simulation of the TOU rate structure, EPEV-H rates are imposed in the summer months (May 1st- October 31st) and EPEV-L rates in the winter (November 1st-April 30th).

The EPEV-H and EPEV-L rates are as defined in Table 3.1. These rates were chosen to map the behavioral response and therefore the environmental consequence of the most extreme incentive structure that could be estimated given the SDG&E experiment data.

In the EPEV-H rate plan, the price ratio between the peak and super off-peak period in the summer months is 6. The high price ratio should offer a stronger price signal to consumers and produce larger shifts in consumer behavior than the current tiered rate plan. On the other hand, the EPEV-L rate has a price ratio of 1.31 offering a weak signal to push vehicle charging to the super off-peak period. In the latter case, as observed earlier in the preliminary analysis of the experiment data, households can be expected to charge their vehicle during the peak and off-peak hours of the day. If workplace charging is available, EV owners can be encouraged to charge their vehicle during the off-peak hours of the day under a rate structure similar to EPEV-L. Additionally, the seasonal variation in the simulated rate structure allows analysis of the emission effects of a more flexible rate plan than the tiered pricing structure or the current EV-TOU rates offered by SDG&E. Change in marginal and total emissions under the TOU rate plan is provided in Table 3.6.

Change in marginal emissions (lb/GWh) is defined here as the difference in CO_2 emissions relating to a unit change in electricity demand under the two pricing scenarios, assuming little or no structural change in the electricity system. In other words, we get a short run estimate of the marginal emission effect of shifting from tiered pricing to TOU rates. A reduction in marginal emissions is observed for all the TOU periods, particularly for the off-peak period. Considering households are getting strong price signals for their usage of electricity under the TOU plan compared to the tiered system, overall energy consumption is more aligned with the marginal cost of production of electricity in both the summer and winter months reducing marginal emissions.

Usually, marginal emissions are high during the early morning hours as base load plants (mostly coal) are ramped up and natural gas plants are turned on to meet the demand in the subsequent peak period. However, with increasing share of solar energy, the dispatch module for the off-peak morning has changed significantly. If there is an increase in load demand during the off-peak hours of the morning in response to the TOU rate in winter months, it can be satisfied with the available solar energy, reducing marginal emissions.

According to the data reported by CAISO on the availability of solar power, the supply of energy increases from 7 a.m. and reaches the peak around noon, but it remains high till 3 p.m. when it drops drastically. In the experiment done by SDG&E, the peak period included a significant portion of the time when emissions are low due to the availability of solar power. In other words, the reduction observed for the peak period might be driven by its definition in the experiment design.

As mentioned above, the dispatch module between noon- 2 p.m. when there is adequate solar energy on most days is significantly different from the set of resources that can be dispatched between 5 p.m. and 7 p.m. in the evening. An increase in load demand in the noon-2 p.m. slot may not increase marginal emissions in those hours, particularly during the winter months, but a rise in demand between 5 p.m. and 7 p.m. would require ramping up natural gas plants or usage of oil leading to higher emissions. When these two periods are combined, the effect on marginal emissions can be misleading. In other words, the environmental benefits of switching to TOU rate will be closely related to the definition of the periods, and how it is aligned with the supply cycle of clean energy resources.

Table 3.6: Difference in Marginal Emissions (lbs/gwh) in the 3 TOU Periods (CAISO Region)

		Winter					Summer					Winter	
	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Base Case: Marginal Emissions (ME)	Super Off-Peak	0.267	0.247	0.174	0.245	0.376	0.392	0.407	0.423	0.421	0.389	0.348	0.394
	Off-Peak	0.255	0.243	0.180	0.240	0.344	0.364	0.383	0.392	0.383	0.358	0.326	0.363
	Peak	0.252	0.238	0.181	0.242	0.340	0.355	0.378	0.387	0.375	0.355	0.323	0.356
	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Scenario I: Marginal Emissions (ME)	Super Off-Peak	0.245	0.172	0.151	0.228	0.289	0.306	0.325	0.374	0.282	0.245	0.238	0.293
	Off-Peak	0.060	0.048	0.043	0.056	0.086	0.091	0.099	0.112	0.090	0.083	0.061	0.070
	Peak	0.075	0.058	0.052	0.071	0.128	0.132	0.142	0.157	0.126	0.117	0.075	0.089
	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Difference in ME (lbs/gwh)	Super Off-Peak	-0.022	-0.075	-0.022	-0.017	-0.087	-0.087	-0.081	-0.049	-0.139	-0.144	-0.110	-0.101
	Off-Peak	-0.195	-0.195	-0.138	-0.184	-0.258	-0.273	-0.284	-0.280	-0.293	-0.275	-0.265	-0.293
	Peak	-0.177	-0.180	-0.129	-0.171	-0.212	-0.223	-0.236	-0.230	-0.249	-0.238	-0.248	-0.267
Difference in Total Emissions (lbs)	Super Off-Peak	-0.0487											
	Off-Peak	0.1135											
	Peak	0.0767											
	Total	0.1415											

[1] The emission amount in lbs was scaled by a factor of 1000 in the regression model for the purpose of analysis. Therefore, the amount for total change in emissions is reported after multiplying the estimated amount by 1000.

In order to get a better understanding of the environmental implications of moving to a TOU plan, the total emission cost of changing the pricing structure from tiered to TOU in the SDG&E area is estimated below and mapped to potential damages in the CAISO region (equation 3.16). Using the EPA social cost of carbon of $41 per ton, the emission cost is estimated to be $0.0025.

$$\varDelta TotalEmissions = \Sigma_{t=1}^{n}(\widehat{Emission}_{base}) - \Sigma_{t=1}^{n}(\widehat{Emission}_{scenario1}) \tag{3.16}$$

$t{=}1,2,\ldots,n$ represents emissions in month m of the sample years 2010-2015.

Given the total reduction in emissions is low in each period, the savings in dollar terms is also small. Nonetheless, considering the reduction in marginal emissions observed in all time periods, particularly in the summer and early winter months there is evidence of environmental benefits of moving from the tiered pricing structure to a TOU rate plan. Further, the decline in marginal emissions during the peak period in the winter months (when households may choose to charge during the peak or off-peak hours of the day) might be affected by the definition of the period in the experiment. As explained earlier, the definition of peak period included time slots with significantly different dispatch modules. As a result, it is not possible to make a statement about the potential benefit of aligning load demand with the supply cycle of solar energy by promoting daytime charging of electric vehicles.

There are several important limitations in the analysis that one should keep in mind while interpreting the results provided in Table 3.6. First, the uncompensated price elasticities are estimated from the behavioral response of EV owners to TOU rates in the SDG&E area while the change in the marginal emissions are for the CAISO region. The peak period for the northern part of the CAISO region starts one hour later compared to the SDG&E area. In other words, when there is additional load demand at 3 p.m., which is peak period in the

SDG&E area, the marginal emissions might reflect off-peak production profile for the CAISO region. Second, the model does not account for trading. If CAISO imports power from dirtier plants to meet load demand during the evening peak hours, the marginal emission estimates in both the scenarios will be downward biased. Third, the elasticity measures are estimated assuming a linear demand curve, and therefore the limitations associated with calculating elasticity for large price changes hold in this case. Finally, the elasticity measures are representative of the response behavior of early adopters of EVs in the SDG&E area. Though the response, and therefore the estimated price elasticities can be expected to be similar to the EV customers in the near future, the extent to which the charging behavior of early adopters would represent that of EV owners, in the long run, is uncertain.

3.6 Conclusion

Electricity pricing will play a major role in encouraging adoption of EVs and in ensuring economical and environmentally optimal charging behavior among existing EV owners. It is necessary to implement a rate structure that would reduce load variation across periods and encourage consumers to use energy efficiently- both for vehicle charging and regular household usage. As evident from the results provided in the paper, a TOU rate scheme that matches cost to the consumer with the time-varying production costs of utilities will lead to lower marginal emissions than the tiered pricing structure that does not penalize users for increasing load demand in the peak period. However, to understand the total economic cost of TOU rates, it is required to analyze the long term effects of the rate structure on household utility bills. Also, as part of future work on this topic, it would be interesting to explore any difference in response behavior to TOU rates applied to the whole household and those applied to EVs. EVs have advanced metering technology built into the car that allows the user to time the energy usage as well as monitor consumption. The same kind of information may not be available to consumers at the household level generating different price responses among consumers.

In California, policymakers and utilities have to opportunity to reduce the concerns related to EV charging behavior by aligning the additional load demand with the supply cycle of solar energy. However, as noted earlier in the paper, the realization of benefits is closely related to the definition of the peak and off-peak hours (morning). If the peak period includes time slots with a significant difference in availability of renewable resources, the TOU rate structure may fail to generate the desired environmental benefits. However, there is an economic and environmental cost of integrating the supply cycle of solar energy into the design of the TOU rate structure. While utilities currently suffering loss due to curtailment of solar energy as well as from purchase of electricity produced from rooftop PV cells at the retail rate will gain by moving the starting hour of the peak period to 3 p.m., it may affect the adoption rate of PV cells and hence, the future supply of solar energy. PV cell owners would suffer an economic loss under the current net metering scheme if the peak period is moved to 3 p.m. This mismatch between economic incentives and environmental costs need to be taken into account in future policy design to maximize the benefits of EV adoption and integration of renewable resource in the power sector.

Overall, in spite of the important limitations in the data and design of the simulation, the analysis provided in the paper contributes towards ongoing policy discussions in California and other states/countries where policymakers are trying to simultaneously decarbonize the transportation and the power sector. TOU rate or flexible CPP plans are usually the proposed solutions to deal with the changing grid structure and increase in load demand due to vehicle charging. Using a unique dataset on consumer response to different TOU rates, this study provides evidence of environmental benefits of moving to a price structure that aligns usage with the time-varying production cost of electricity. The analysis of marginal emissions in the different TOU periods in summer and non-summer months also bring forth the importance of accounting for the supply cycle of renewable resources in the definition of the periods in the rate plan.

In future extensions of this paper, electricity trading will be taken into account to get more accurate estimates of the environmental effect of TOU rates in the CAISO region. Additionally, the analysis will be done using an electricity dispatch model such that alternative supply and demand scenarios can be modeled and a number of key regional market outputs like the average and marginal price of electricity, generation adequacy can be calculated along with the emission effects.

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Appendices

Chapter 1: Adoption of Alternative Fuel Vehicles: A Stated Preference Analysis of Personal Vehicle Transaction Choice

Chapter 2: Policy Dilemma: Road Pricing or Road Space Rationing- A Case Study of Santiago, Chile

Chapter 3: Time-of-use pricing and EV charging behavior-Environmental Impact of Day-time Charging

Appendix A

Chapter 1 Appendix

A.1 Choice Experiment: Vehicle Attributes

Each of the eight discrete choice experiments offered to a household had four hypothetical vehicle options. The vehicle options differed across the following dimensions (Table A.1). The values for each of the vehicle attributes were representative of the preferences outlined by households in round one of the California Vehicle Survey.

Table A.1: Vehicle Attributes

Vehicle Attribute	**Definition**
Vehicle Type	Small Car, Mid-size or Full-size Car, Sport Car,SUV, Minivan, Van, Pick-up Truck
Fuel Type	Gasoline, Hybrids, Flex-fuel, Battery Car, Hydrogen Cell Car, CNG, Diesel
Vehicle Models Available	Number of other vehicle makes available with similar features.
Model Year	Model year of the vehicle. Ranges from 1992 to 2013.
Vehicle Price	Final retail price of the car after dealer incentive or discount. Tax, title, tag not included.
Incentives	HOV lane access, Free parking, Tax credits and Rebates.
MPG or MPGe/Fuel Economy	Number of miles per gallon. Assumes 55 percent city and 45 percent highway driving.
Cost per 100 Miles	Fuel cost for driving 100 miles. (Fuel price*gallons per mile*100)
Refueling Station Availability (in minutes)	Time taken to reach the refueling station. The reference point was taken to be home.
Refueling Time (in minutes)	Amount of time taken to refuel the vehicle at the station
Vehicle Range	Maximum distance the vehicle can travel on a full tank or full charge without refueling.
Trunk/Cargo Space:	Measured in cubic feet.
Acceleration	Amount of time, in seconds, it takes to accelerate vehicle from 0-60 mph.
Annual Maintenance Cost	Cost of routine oil and filter changes. Does not include insurance, and registration fees.

A.2 Willingness to Pay for Alternative Fuel Vehicles: Owners of New Technology Vehicles

The willingness to pay for alternative fuel vehicles among the current owners of new technology vehicles is given in Table A.2. It is observed that owners of new technology vehicles are usually willing to pay rather than be compensated to move from a gasoline car to an alternative fuel vehicle. However, it should be kept in mind that the sample of alternative fuel vehicle owners is relatively small and the results may not be representative of the population.

Table A.2: WTP measures of Households with Alternative Fuel Vehicles

Households with Alternativeel Vehicles				
Vehicle Category		Income<$50 K	$50 K<Income<$150 K	Income>$150 K
Hybrid Fuel Technology	Car	-0.015	-0.016	-0.162
	SUV	0.861	0.267	0.368
	Van	-0.087	-0.852	-1.086
	Truck	-0.104	-0.903	-1.256
New Technology CNG, HFCV, Battery	Car	-0.088	-0.093	-0.937
	SUV	-0.088	-0.684	-0.941
	Van	-0.150	-1.468	-1.870
	Truck	-0.139	-1.207	-1.678
Diesel, Bi-Fuel, Flex Fuel	Car	-0.103	-0.109	-1.908
	SUV	-0.019	-0.149	-0.205
	Van	-0.118	-1.148	-1.462
	Truck	-0.041	-0.355	-0.494

Appendix B

Chapter 2 Appendix

B.1 Review of License Plate based Driving Restriction Policy in other Developing Countries

(a) *Mexico City, Mexico*

'Hoy no Circula' was started in late 1989, and consisted of prohibiting the circulation of 20% of vehicles from Monday to Friday depending on the last digit of their license plates. The program was planned to apply only during the winter, when air pollution is at its worst. During the winter season, thermal inversion, an atmospheric condition which traps smog and pollution close to the ground, increases air pollution noticeably. The program was made permanent at the end of the 1990 winter season. Due to concerns over the rising air pollution in Mexico City, the driving restriction was coupled with an exhaust monitoring program, whereby a car's pollutant emissions are analyzed every six months. A sticker is affixed to each vehicle following an emissions test, indicating whether a vehicle is exempt from the program or not. The driving restriction is meant to reduce the emissions that lead to ozone build-up in the city.

(b) *Sau Paulo, Brazil*

The scheme 'Rodzio veicular' was first implemented in 1995 as a trial on a voluntary basis, and then as a mandatory restriction implemented in August 1996 to mitigate air pollution. Thereafter, it was made permanent in June 1997 to address traffic congestion. The driving restriction applies to passenger cars and commercial vehicles, and it is based on the last digit of the license plate. Two numbers are restricted to travel every day between 7 a.m. to 10 a.m. and 5 p.m. to 8 p.m. from Monday through Friday. Vehicles exempted from the restriction include buses and other urban transportation vehicles, school buses, ambulances and services vehicles. After 2014, plug-in hybrid electric vehicles and fuel-cell vehicles with a license plate registered in the city were also exempted.

(c) *Bogota, Colombia*

Vehicle restriction program 'Pico y Placa' was implemented in Bogota in 1998 to mitigate traffic congestion. Although the measure was proposed as a provisional one, it ended up being adopted permanently by the city. Initially 20% of the vehicles were restricted from circulating in specific urban areas based on their license plate number between 7:00 a.m. and 9:00 a.m. and between 5:30 p.m. and 7:30 p.m. Currently, the restriction spans the entire day from 6:00 a.m. to 8:00 p.m. The extension of hours is mainly done to prevent commuters from substituting their travel time to avoid the restriction.

(d) *Quito, Ecuador*

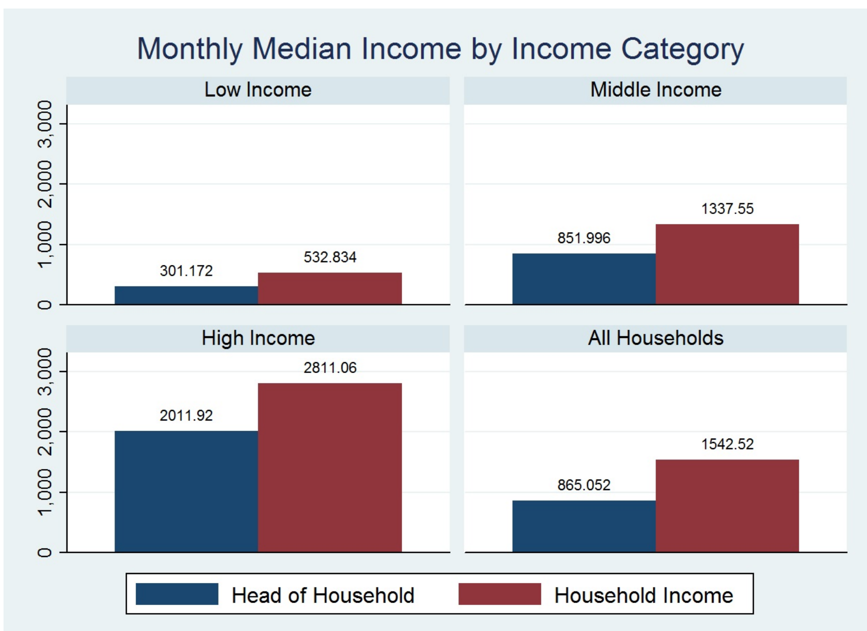
'Pico y Placa' went into effect in Quito, Ecuador in 2010. The main objective was to reduce congestion in specific parts of the city during peak hours. Hence, based on the last digit of their license plate number, vehicles are restricted to access the central part of the city during weekday peak traffic hours: 7-9:30 a.m. and 4-7:30 p.m. The other objectives of the policy are to reduce emissions and reduction in gasoline and diesel consumption in order to lower government expenditure on fuel subsidies.

(e) *Beijing,China*

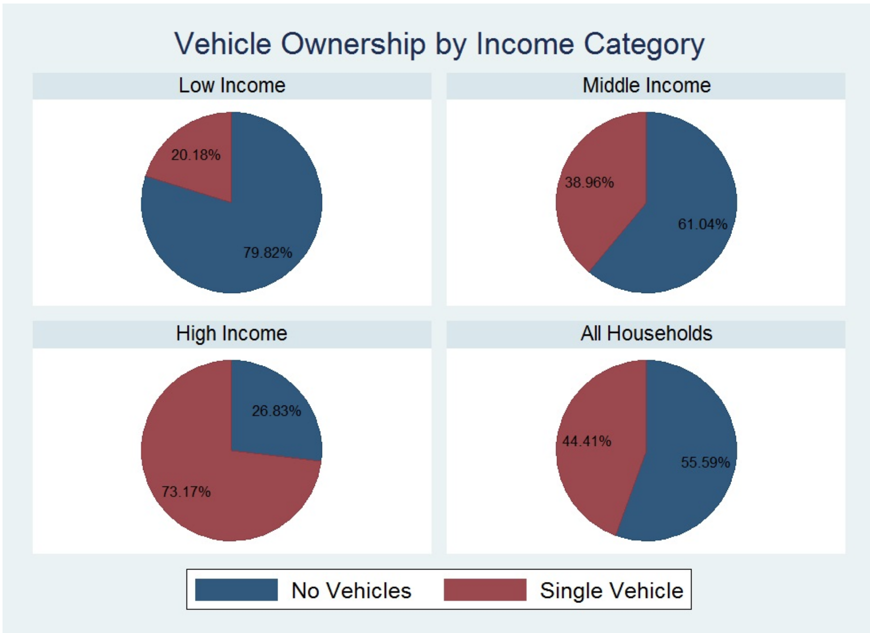
Road space rationing in Beijing was introduced on a permanent basis after successful results were obtained during the 2008 Summer Olympics. The restriction applies to all private vehicles based on the last digit of the license plate number. 30% of government and corporate vehicles are also restricted on each weekday. The main objective of the policy is to reduce vehicle emissions in the city.

B.2 Income Distribution and Vehicle Holding of the Sample of Head of Households of Zero- and One-vehicle Households

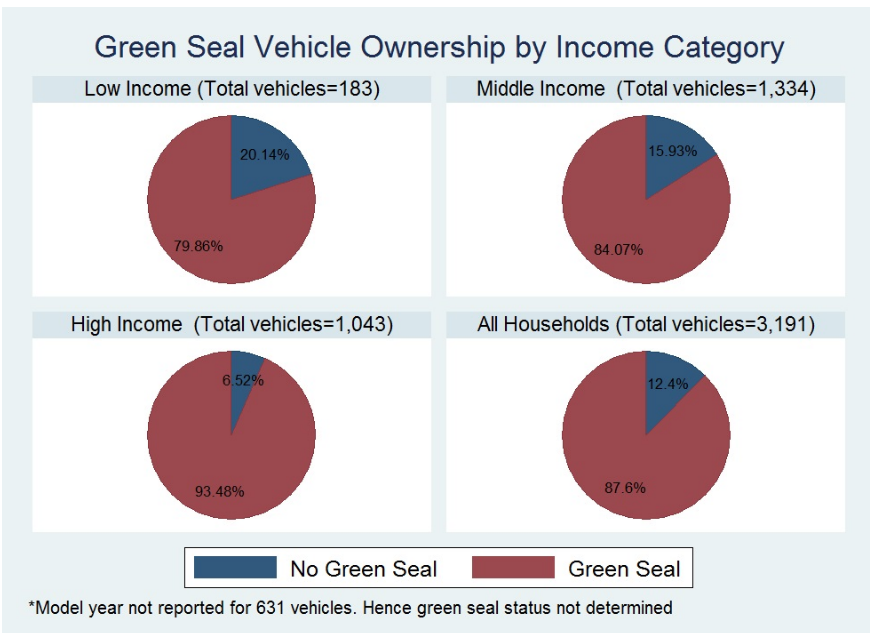
Figure B.1: Median Income (in USD)



(a) Vehicle Holding by Income Category



(b) Share of Non-catalytic converter Vehicles by Income Category



Appendix C

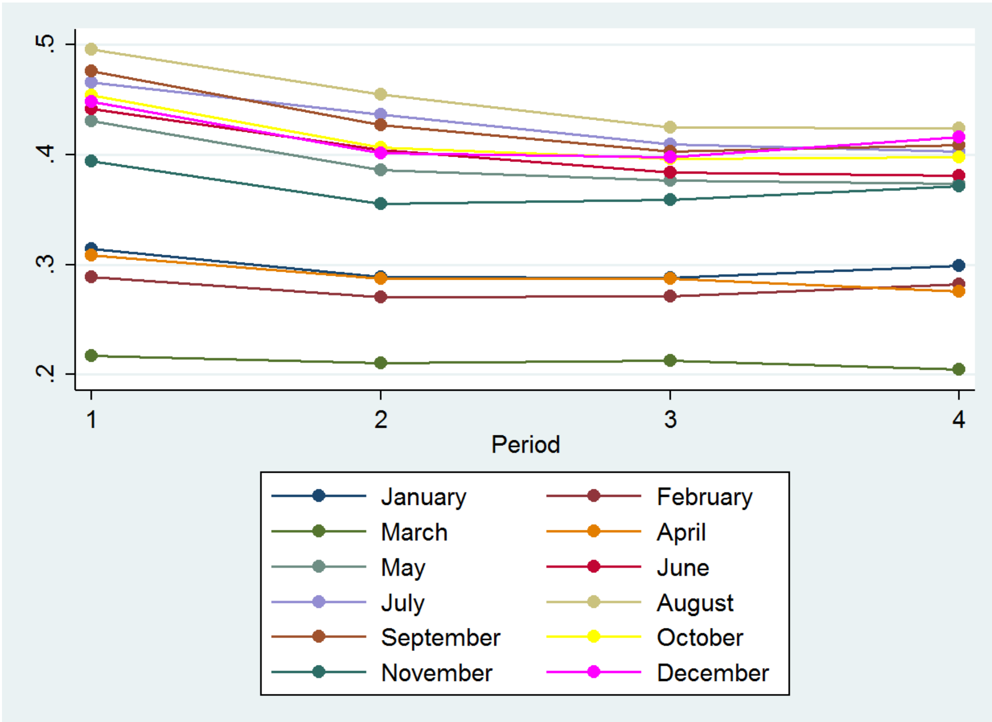
Chapter 3 Appendix

C.1 Marginal Emissions During Proposed TOU Periods (by SDG&E) in the CAISO Region

Table C.1: Marginal Emissions of Carbon Dioxide (in tons): Time-of Use Periods by Month in CAISO Region

	Period	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
Weekday	Super Off-Peak	0.314	0.289	0.217	0.308	0.431	0.442	0.466	0.496	0.476	0.454	0.394	0.449
	Off-Peak (mor)	0.288	0.270	0.211	0.287	0.386	0.405	0.437	0.455	0.427	0.406	0.356	0.402
	Peak	0.288	0.271	0.212	0.287	0.377	0.384	0.409	0.425	0.403	0.396	0.359	0.398
	Off-Peak (eve)	0.299	0.282	0.204	0.276	0.374	0.381	0.403	0.424	0.409	0.397	0.372	0.416
All Days	Super Off-Peak	0.320	0.303	0.231	0.341	0.398	0.424	0.428	0.466	0.447	0.423	0.385	0.419
	Off-Peak (mor)	0.295	0.283	0.222	0.316	0.364	0.396	0.412	0.436	0.410	0.386	0.350	0.380
	Peak	0.293	0.284	0.226	0.315	0.356	0.376	0.386	0.408	0.387	0.378	0.354	0.377
	Off-Peak (eve)	0.305	0.295	0.218	0.305	0.350	0.371	0.376	0.404	0.389	0.375	0.365	0.393

Figure C.1: Marginal emissions of Carbon dioxide (tons) in 4 periods of the month (Weekdays)



C.2 QUAIDS Model Estimates using Poi (2012) program

The dummy variables representing treatment month for each household and season are included as demographic variables in the model. Column I and II has the uncompensated and compensated price elasticity measures while in column III the expenditure elasticity measures evaluated from the estimates of the QUAIDS model are reported.

Table C.2: Expenditure and Price Elasticities (Weekday)

	Uncompensated Price Elasticity (I)			Compensated Price Elasticity (II)			Expenditure Elasticity (III)
	Peak	Off-Peak	Super Off-peak	Peak	Off-Peak	Super Off-Peak	
Peak	-0.77	-0.48	-0.68	-0.52	-0.27	0.79	1.94
Off-Peak	-0.52	-0.59	-0.39	-0.32	-0.43	0.75	1.50
Super Off-Peak	0.04	0.02	-0.83	0.13	0.11	-0.24	0.76

[1] The elasticities are based on the output of the QUAIDS model estimated using the program developed by Poi.B (2012)

[2] Row 'i', column 'j' of each elasticity matrix represents the percentage change in the quantity of good 'i' consumed for a 1% change in the price of good 'j'.

[3] The $\alpha_0 = 2$ in the model.