The impact of California's inefficiently high electricity prices on electric vehicle adoption in low-income communities

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Abstract

The main Investor-Owned Utilities in California charge electricity prices that are way above the social marginal cost of consuming electricity. This results in economic inefficiency which previous studies prove to have negative implications for inequality and to slow down the electrification of the transportation sector. This paper seeks to build on the existing knowledge by investigating how the high electricity prices affect low and high income households' electric vehicle adoption differently in California, and it aims to quantify the extent of such difference. The results show that EV adoption among low income households would be considerably higher under efficient retail pricing, and that low income households are more negatively affected than their high income counterpart. However, the results relative to high income households specifically are inconclusive, and therefore the extent to which the two income groups are affected differently cannot be determined. Further research should tackle this issue by including additional variables such as income by year and EV quality, as well as more granular gasoline price data.

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1 Introduction

The transportation sector is a huge environmental threat in the U.S., representing the largest contributor to greenhouse gas (GHG) emissions as it makes up 33% of the total (US Department of Transportation, 2023). For this reason, it's decarbonization through wide spread electric vehicle (EV) adoption plays a central role in the overall battle against climate change. In order to reduce the emissions related to the transportation sector, the Biden Administration has approved a $174 billion investment in the EV market as part of the American Jobs Plan (The White House, 2021).

When making the decision to buy a new car, consumers consider two factors: the up-front purchase cost of the vehicle and the cost of owning it, that is the average cost of fuel over a given time period. While the higher up front price of EVs with respect to internal combustion engine vehicles (ICEVs) represents a financial deterrent, EVs have lower fuel and maintenance costs to their advantage. Because EVs are cheaper to maintain and drive, over time the higher up front cost is recovered and consumers end up saving money in the long run. However, the time it takes consumers to recover the upfront cost depends on the electricity prices at a given location. Borenstein and Bushnell (2021) find that in many parts of the US, electricity prices are actually too high, averaging way above the social marginal cost (SMC) of consuming electricity. In these places, among which are California and the North East, the high electricity prices might hold consumers back in their decision to purchase an EV, as the long term savings represented by the cheaper fuel cost are diminished. In California for instance, it currently takes almost seven years to make up for the up front cost of an EV[1], but if retail electricity prices were efficient, that is if they equaled the social marginal cost of consuming electricity, potential buyers would recover their initial investment in 4 years and a half, which would result in more people considering the zero-emission option.

This paper focuses on California, where the reason why electricity prices are set way above the social marginal cost of electricity is the three main Investor-Owned Utilities (IOUs) in the state – Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E)– recovering their operational costs by reversing them onto consumers. As a consequence, the cost of owning an EV is set above the social optimum resulting in a slow down of the electrification of the transportation sector and disproportionately affecting low-income households for three main reasons. First, as high income households become energetically self-sufficient, the pool among which the IOUs operational costs are recovered becomes smaller and predominantly low income (Borenstein, Fowlie, and Sallee, 2021). Second, low income consumers already spend a higher share of their paycheck

[1]The calculations I did and assumptions I made are explained in the Appendix section and shown in tables 7 and 8.

to cover their electricity bill, and therefore they are more intensively affected by high prices (Borenstein, Fowlie, and Sallee, 2022). Finally, like Muehlegger and Rapson (2021) find, lower income households are more elastic to electricity prices than high income households, which implies that low income consumers' demand for EVs will be more elastic to changes in prices both related to the up-front purchase cost and the cost of owning an EV. Because low income consumers are more adversely affected by the high electricity prices and they are also more elastic to prices in general, the inefficient retail prices that IOUs charge not only represents a hurdle for widespread EV adoption in California, but also – and most importantly – an obstacle for widespread EV adoption among low income consumers. This ultimately results in an inequality issue on top of an economic inefficiency issue, and is in contrast with the ambitious goal that California has set of achieving 100% of zero emission vehicles (ZEV) sales by 2035 (California Air Resources Board, 2022).

The current literature agrees on the negative correlation between EV adoption and electricity prices. For instance, (Bushnell, Muehlegger, and Rapson, 2022) find that a one cent increase in electricity prices is correlated with a 0.4% decrease in EV adoption; and Borenstein et al. (2022) conclude that recovering non-incremental costs through higher retail electricity rates increases EV charging costs and substantially slows the pace at which the transportation sector is electrified. This paper seeks to expand on the existing knowledge about the relationship between electricity prices and EV adoption by differentiating between the effect that California IOUs electricity prices have on high and low income consumers' EV adoption. Additionally, this paper seeks to quantify the predicted EV adoption level under efficient retail electricity prices for both high and low income consumers in order to shed light on the extent to which the EV market growth is in fact hindered, and how this differs by income.

The electricity and gasoline price data used in this study come from the US Energy Information Administration, The EV registration data is collected from the California Energy Commission, and the income and population count data is retrieved from the US Census Bureau. The different data sets are merged together to obtain a balanced panel data set at the zip code and yearly level that covers the time period from 2009 to 2021. The paper employs a variety of panel fixed effects regression models to investigate the relationship between EV adoption and IOUs electricity for the two income groups. The empirical strategy is divided in two main parts – one in which only electricity prices are considered as the explanatory variable and one that also includes gasoline prices.

I find that EV registration in low income zip codes in 2021 would be considerably higher under efficient electricity retail pricing both when electricity prices only are considered and also when gasoline prices are introduced in the model. However, the relationship between EV adoption and electricity prices in high income zip codes appears to be driven by an upward sloping demand curve in both parts of the study. Therefore, the results related to zip codes characterized as high income are inconclusive. This may be attributed to the fact that other variables that have an effect on EV adoption are changing differently between time and space and are therefore not captured by the models' fixed effects. Future research should include additional explanatory variables such as EV quality and income by zip code in order to prevent omitted variable bias.

Overall, this paper successfully proves that IOUs electricity prices greatly hinder EV adoption of low income households and that the effect is greater than that of high income households. This is relevant because it shows that the regressivity of the current electricity market in California translates into regressivity of the EV market as well. To ensure that the state's goal of decarbonization of the transportation sector is achieved and that lower income households are not left behind in the process, California should thoughtfully consider adopting policies to best approximate an efficient electricity market in which the retail prices consumers face get as close as possible to the social marginal cost of consuming electricity.

2 Literature Review

Borenstein and Bushnell (2021) provides the foundation to my thesis question by exploiting the inefficiently high electricity prices that California's Investor-Owned Utilities charge and by comparing them to the rest of the country. The paper examines the US electricity industry from 2014 to 2016 by analyzing the relationship between the marginal retail prices and the social marginal cost of supply. The study calculates the social marginal cost of consuming electricity in California by averaging the private marginal cost and the social marginal cost. Although the private marginal cost is among the higher in the country – mostly between 3.83 to 4.20 cent per kWh – the external marginal cost is much lower than most of the US – between 2.53 and 3.19 cent per kWh – due to the clean grid that characterizes California. As a result, California has among the lowest SMCs in the US. In order to estimate the dead-weight loss (DWL), Borenstein and Bushnell compare the social marginal cost to the marginal price of electricity, which in California mostly ranges between 16 to 41.2 cent per kWh. The difference between the marginal electricity price and the average social marginal cost in California is among the highest in the country together with parts of New England 8. After normalizing each quantity of kWh to the one utilities would have sold if price equaled SMC, the paper calculates that California's three large investor-owned utilities together make up 8% of the total US residential normalized quantity of kWh demanded, but are responsible for 31% of the total DWL.

Borenstein et al. (2021) argue that California IOU's prices are high by both historical and national standards, in fact SCE charges prices that are 45% higher than the national average, PG&E about 80% higher, and the most expensive SDG&E prices are roughly double the national average. The report estimates the marginal cost of electricity by considering all the following factors: the cost of generating additional electricity, potential increases in the cost for transmission and distribution capacity that scale with usage, the potential need for additional generation capacity, and the cost of GHG emissions borne by society. The results show that marginal cost is greatly lower than electricity rates, which exceed the social marginal cost by two to three times. It follows that problematic incentives are created, since over-pricing sends misleading signals about the true cost to society of consuming electricity, discouraging its usage and causing DWL from under-consumption.

Diving deeper into how the high IOUs electricity rates affect the electrification of the transportation and residential sectors, Borenstein et al. argue that such is discouraged by the massive gap between the marginal cost that IOUs face and the retail price they charge consumers. The gap has the same effect, and therefore can be defined as, an electricity tax, and it leads to economic inefficiency. Borenstein et al. (2022) estimate that the annual operating costs of driving an EV are on average $600 higher than the social marginal cost, and the cost reaches a high of $900 for San Diego Gas & Electricity' customers. The authors conclude that the increased cost of driving an EV not only slows the pace at which the transportation sector is electrified, but it also nearly neutralizes the subsidies implemented to incentivize EV adoption.

In addition to an economic inefficiency issue, the tax on electricity represents an equity issue for two main reasons. First, as higher income households are increasingly shifting to solar PV panels and becoming energetically self-sufficient, the burden of the operational costs that IOUs face is covered by a base that is increasingly smaller and predominantly made up of lower and middle-income households (Borenstein et al., 2021). Second, the tax is regressive because lower income households pay a much larger share of their earnings in electricity costs than higher-income households do (Borenstein et al., 2022).

Bushnell et al. (2022) tested how the electricity and gasoline prices in California affect the marginal electric vehicle buyer's decision to purchase an EV. The authors estimate a coefficient for their dependent variable using two different regressions. In the first one they look at how electricity and gasoline prices affect EV adoption while controlling for the fixed effects of time and space, that is for the differences in moths and block census groups respectively. The results show that a one cent increase in volumetric electricity prices is associated with a monthly fall in EV demand of about 0.4%, and that a one cent increase in gasoline prices is associated with a 0.5% monthly rise in EV demand. To compare the coefficients in a meaningful way, the authors introduce the concept of engine efficiency by considering a Toyota Camry, an ICE that gets 30 miles-per-gallon, and a Tesla Model 3, which gets 4 miles-perkWh. The analysis estimates that consumers value gasoline price eight times more than electricity prices when deciding whether to purchase an EV. The second regression model insulates the effect of electricity prices by focusing the analysis on census blocks located along the utility service territory boundaries, where households face similar commutes and benefit from similar public charging infrastructure but they potentially face very different electricity prices. When controlling for observable demographic characteristics of the census block, the relationship between electricity prices and EV sales appears again to be negative and significant. Bushnell et al. (2022) estimate that EV adoption would be 13% higher under efficient electricity pricing and 33% higher when considering households living close to a service territory boundary, the larger estimate is due to those households being on average wealthier and less likely to live in multi-unit dwellings.

Previous studies agree on the negative relationship between EV adoption and electricity prices, and on the positive relationship between EV adoption and gasoline prices and income. Soltani-Sobh, Heaslip, Stevanovic, Bosworth, and Radivojevic (2016) conducted a cross-sectional time series analysis to examine the effectiveness of state incentives and other socio-economic factors in promoting EV adoption in the US. The authors confirm the hypothesis that EV share increases as income grows. They also find a statistically significant and negative relationship between EV share and electricity prices, and positive between EV share and gasoline prices. Sheldon, DeShazo, Carson, and Krumholz (2017) studied the factors affecting PEV sales in California and found that PEV purchases are positively correlated with gas prices and that sensitivity to gas prices has increased in recent years, although the results show no evidence of higher gasoline price sensitivity in lower income regions.

3 Background and Data

3.1 Background

This paper focuses on the effect that the electricity prices charged by Investor-Owned Utilities in California have on electric vehicles. IOUs are privately owned, they issue stocks owned by shareholders, and are larger than Publicly Owned Utilities (POUs), which are instead run by government agencies and political subdivisions (EIA, 2019). IOUs provide electricity to almost three fourth of US consumers, and the two largest ones in the US are Pacific Gas and Electric and Southern California Edison, which count 5.48 and 5.07 million consumers respectively (EIA, 2019). There is a total of six IOUs in California: Bear Valley Electric Service, Liberty Utilities, Pacific Corp, Pacific Gas & Electric, San Diego Gas &

Electric, and Southern California Edison. Figure 1 shows the area in which each operates. This paper focuses on the three largest ones - PG&E, SCE, and SDG&E.

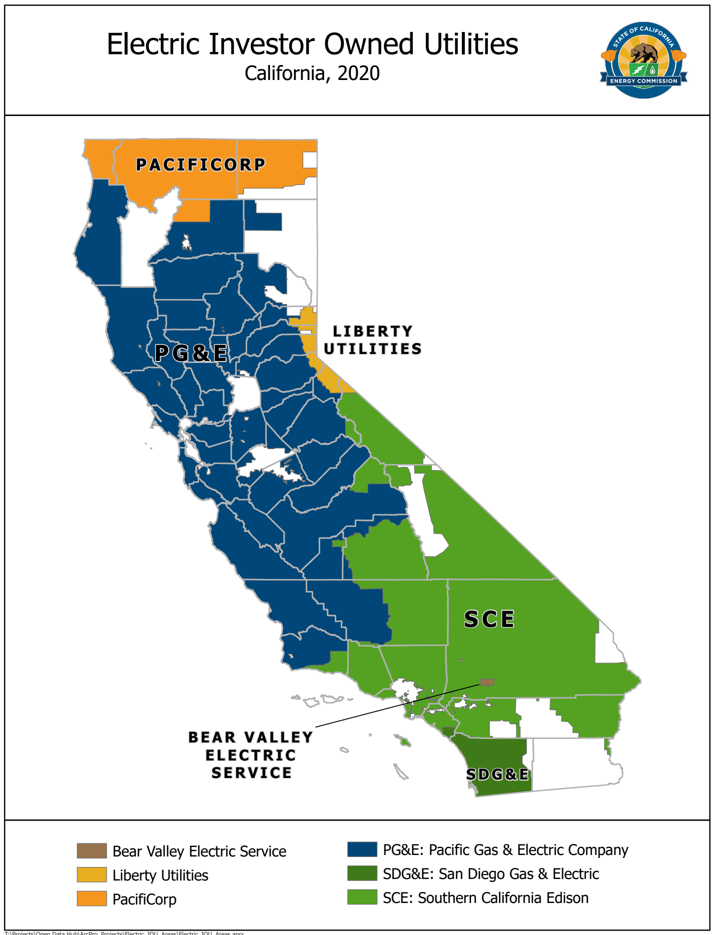

Figure 1: California IOUs Map (California Energy Commission, 2022a)

The electric vehicle market is evolving rapidly and there are currently four different types of electric vehicles available: Battery Electric Vehicles (BEVs), Plug-In Hybrid Electric Vehicles (PHEVs), Hybrid Electric Vehicles (HEVs), and Fuel Cell Electric Vehicles (FCEVs) (US Department of Transportation, 2022). HEVs and FCEVs cannot be recharged from external sources and are not capable of operating with zero tailpipe emissions. In fact, HEVs are powered by a combination of internal combustion engine and electric motors – which uses energy stored in batteries (US Department of Energy) – and FCEVs power an electric motor through a highly efficient electrochemical process that converts hydrogen into electricity (US Department of Transportation). BEVs and PHEVs are recharged by an external power and they differ in that, whereas BEVs run only on electricity, PHEVs also incorporate a smaller internal combustion engine that can recharge the battery or even directly power the wheels (US Department of Transportation). My analysis focuses on BEVs only and from now on I will use the term EVs and BEVs interchangeably.

Like Bushnell et al. (2022) explain, the multitude of potential prices EV owners may pay – linked to the potential charging locations such as home, work, or public charging infrastructure — and the variety of prices they may face at each location, represent one of the major challenges in understanding the effect of electricity prices on EV demand. Bushnell et al. conclude that the majority of EV owners charge their vehicles fully or partially at home via their home master electricity meter. In this paper I assume that EV owners charge their vehicle in an area powered by the same utility that operates in the zip code in which their vehicle is registered, whether that is at home or at a public charging infrastructure, and that consumers pay the average electricity price charged annually by that utility.

3.2 Dataset Building

I constructed a panel data set that contains annual data from 2009 to 2021 at the California zip code level. The main variables present in the dataset are EV registrations and electricity prices – both collected at the annual and zip code level – average population data count and median households income in 2021. The final electricity data set after eliminating outliers contains a total of 15,353 observations, that is data for 1,181 zip codes each year, with each zip code appearing 13 times. Out of the zip codes, 740 are powered by PG&E territory, 335 by SCE, and 106 by SD&E. The summary statistics of the electricity price data set are displayed in table 1. I built a second data set – energy prices data set – containing both electricity and gasoline prices. I added annual gas prices for zip codes corresponding to the PG&E and SCE areas to the initial electricity prices only data set. As SDG&E zip codes are not included in the gas data set, 1,378 data points are dropped and the new energy price data set contains a total of 13,975 observations. Table 2 displays the summary statistics of the energy prices data set.

I retrieved data on the yearly average electricity prices of the three IOUs from the US Energy Information Administration. More specifically, I divided the electric revenue from retail sales by the disposition of retail sales from the operational data sheet for each year, obtaining the average electricity prices charged by the IOUs in any given year. I then adjusted the electricity prices for inflation using 2021 as the base year and I matched each IOU with the zip codes it powers to obtain the yearly retail electricity prices at the zip code level. The graph at the top in Figure 2 shows the variation in the growth of electricity prices over time by utility. The ranking of electricity prices across utilities corresponds to that of the average annual electricity cost premium for EVs across utilities calculated by Borenstein et al. (2022), which finds that SDG&E has the highest premium close to $900, followed by PG&E at about $700 and SCE at $400.

I gathered data on BEV registration by zip codes from the California Energy Commission, which is a reasonable approximation of data on BEV sales by zip code. Therefore from now on, I will use the terms EV registration and EV sales equivalently. I collected population data count from the US Census Bureau, more specifically from American Community Survey which offers data sets on population count updated every five years. I averaged the data from 2011 to 2015 with the data from 2016 to 2020 to estimate the average zip code's population over the time frame covered in my data set. I normalized the EV registration count data by dividing it for the population count and therefore obtaining EV registration per capita. In addition, to account for the growth in EV registration over time, I calculated the cumulative sum of EV sales per capita. The graph at the bottom in figure 2 depicts the growth in the cumulative sum of EV registration per capita by utility.

Figure 2 provide a preview of the relationship between the utilities' electricity prices and EV registration. SDG&E consistently charges the highest electricity prices out of the three IOUs over the entire time period. As expected, the zip codes powered by SDG&E have the lowest EV registration count and growth over time. The areas powered by Pacifc Gas and Electric experience the highest EV registration count regardless of PG&E charging the highest electricity prices out of the three IOUs. This could be due to third factors such as higher income on average in the areas powered by PG&E. Finally, Southern California Edison charges the lowest electricity prices and places second after PG&E in EV adoption over time.

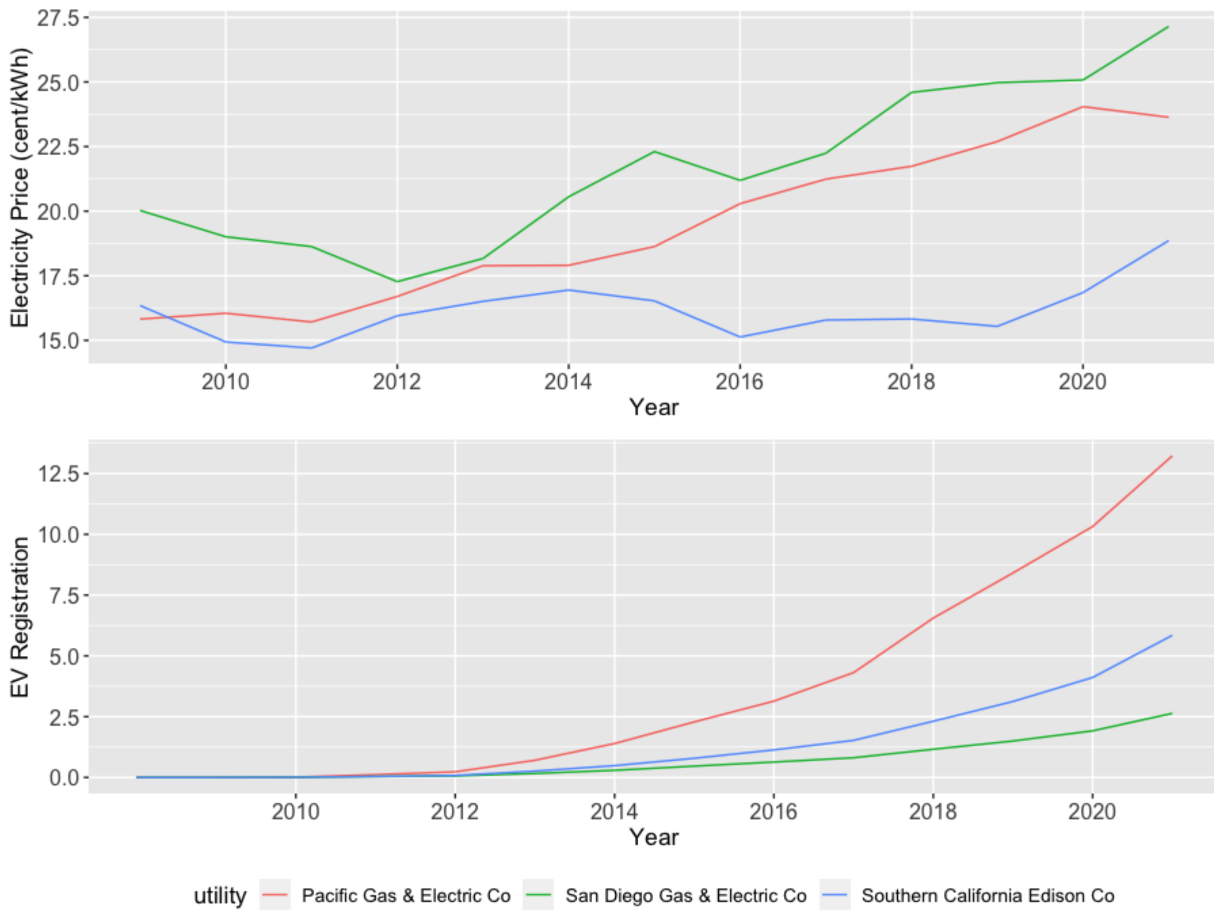

Figure 2: IOUs prices vs EV registration over time

I retrieved data on the median household income by zip code from the US Census Bureau, particularly from the table with code B19013, which displays an average data of 2021 in 2021 inflation-adjusted dollars. The distribution of income is skewed to the right, as shown in figure 9 and the mean is $87,023.58. I determined high and low income zip codes as any income respectively above and below the mean. Out of the 1,181 total zip codes present in the data set, 678 are defined as low income and 503 as high income zip codes. For each income group I created a binary variable. Figure 3 shows that EV adoption took off in 2013 and since then EVs have been increasingly registered in neighborhoods characterized as high income over low income ones. Additionally, figure 10 shows that the relationship between EV sales and income in 2021 is strong and positive.

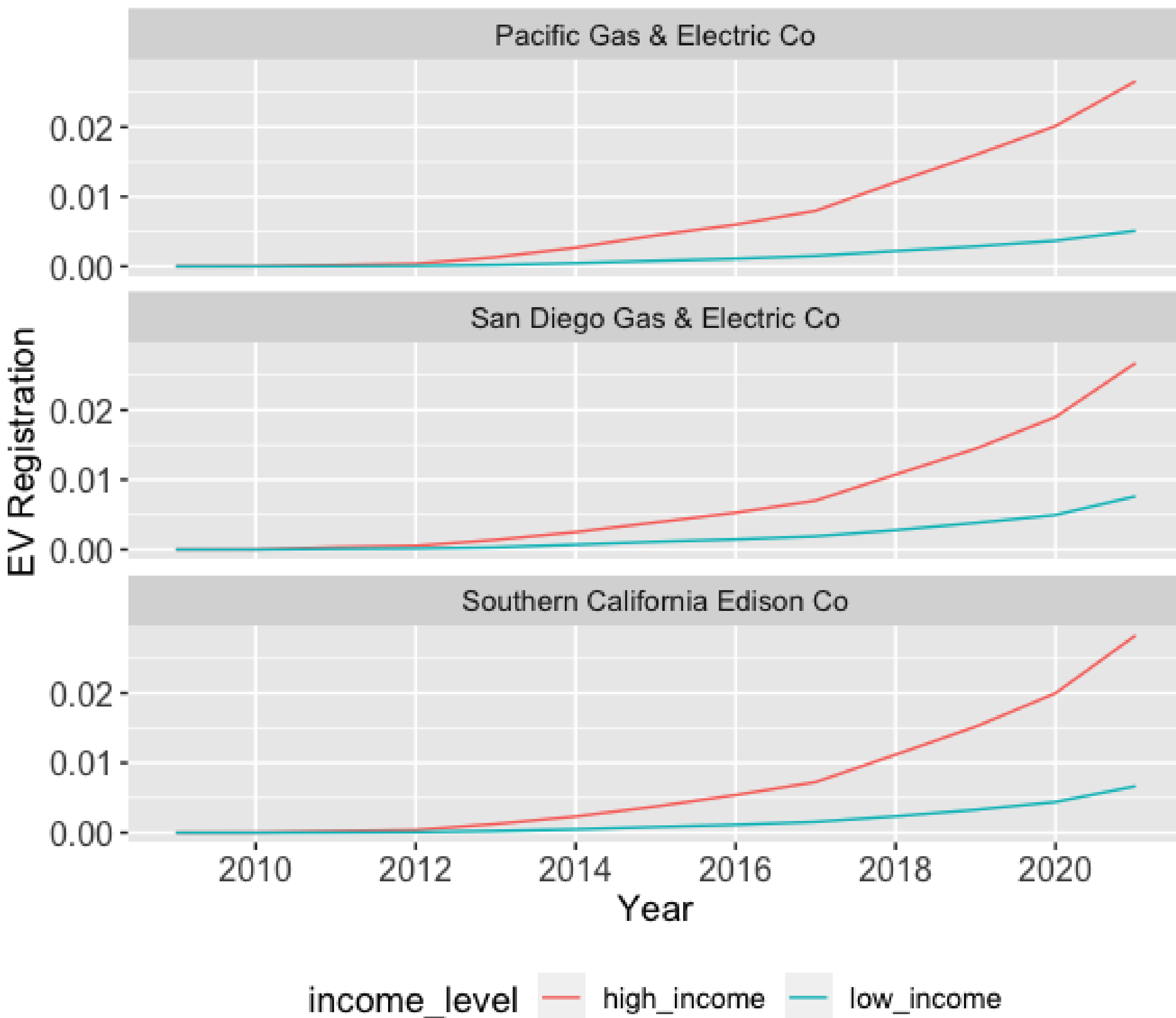

Figure 3: EV adoption by income level and IOUs

Table 1 contains the summary statistics of the main variables in the electricity data set by IOUs.

	PG&E		SCE		SDG&E	
Zip Codes	740		335		106	
	mean	**sd**	**mean**	**sd**	**mean**	**sd**
Population	18,842.33	19,883.56	37,272.6	21,502.49	34,974.24	21,257.14
Income	86,180.62	39,247.01	85,715.95	30,173.06	97,040.95	29,192.29
Electricity Prices (cent/kWh) - Total	19.411	2.910	16.147	1.039	21.631	2.961
Electricity Prices (cent/kWh) - 2021	23.636	0	18.860	0	27.151	0
EV per capita - Total*	10.438	21.393	12.361	23.971	14.88	23.947
EV per capita - 2021*	33.899	39.259	48.813	48.303	57.748	42.368
% of Low Income Zip Codes	0.605	0.489	0.564	0.496	0.387	0.487
EV per capita (Low Income) - 2021*	14.198	17.824	22.568	18.480	26.688	20.807

*EV registration is cumulative sum per capita per 10,000 population

Table 1: Electricity Prices Data Set - Summary Statistics

I collected yearly retail gasoline prices for the cities of San Francisco and Los Angeles from the US Energy Information Administration website. I adjusted the data in 2021 dollars and I assigned the San Francisco retail gasoline prices to the zip codes powered by PG&E, and the gasoline prices in LA to the zip codes powered by SCE, as the areas approximately overlap. Now that the data points for SDG&E are dropped, there is a total of 1,075 zip codes, 5,694 of which characterized as high income and 8,281 as low income. Figure 4 shows the growth in gasoline prices by utility area. There appears to be nearly zero variation among the two region's gasoline prices in any given year.

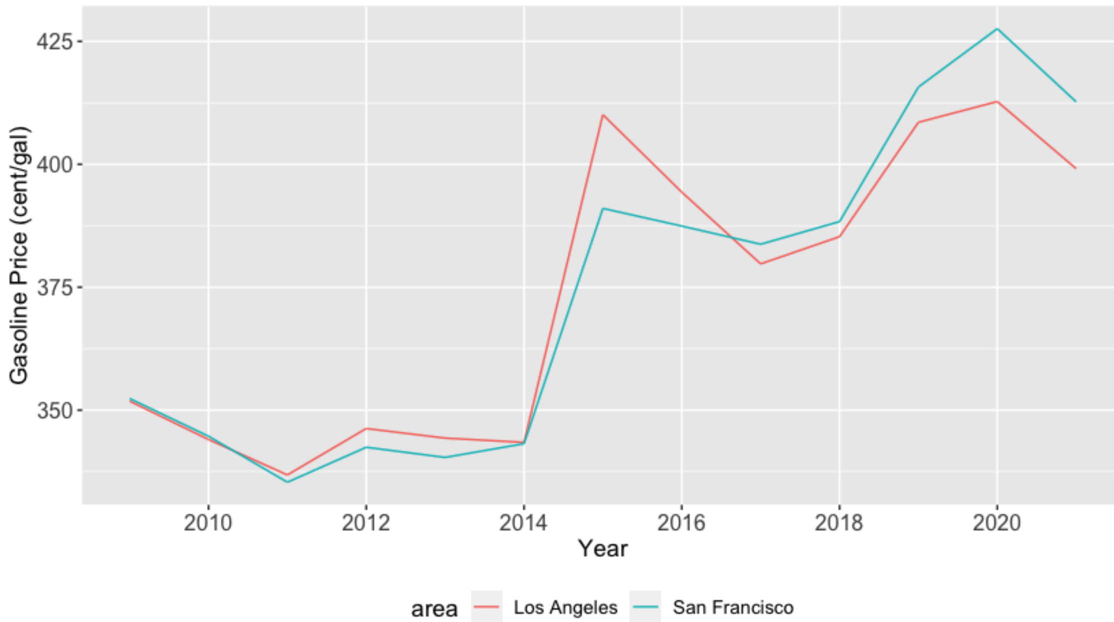

Figure 4: Gas prices over time by area

Finally, to compare the electricity and gasoline prices, I multiplied the two by the average kWh and gallons needed to drive one mile respectively in order to transform them in the same unit of measure – one cent per mile. The values correspond to 0.33 kWh for EVs[2], and 0.045 gallons for ICEV[3]. Additionally, I computed the ratio between the cost to drive one mile in an EV and the cost to drive one mile in an ICEV. The ratio indicates the relative cost to drive an EV with respect to an ICEV. Figure 6 shows that it has been consistently more expensive to drive an EV in San Francisco than in Los Angeles, with the gap increasing in 2015 but getting smaller since 2020. Table 2 provides a summary statistic of the newly added variables.

[2](Eco Cost Savings, 2022)

[3](Idaho National Laboratory, n.d.)

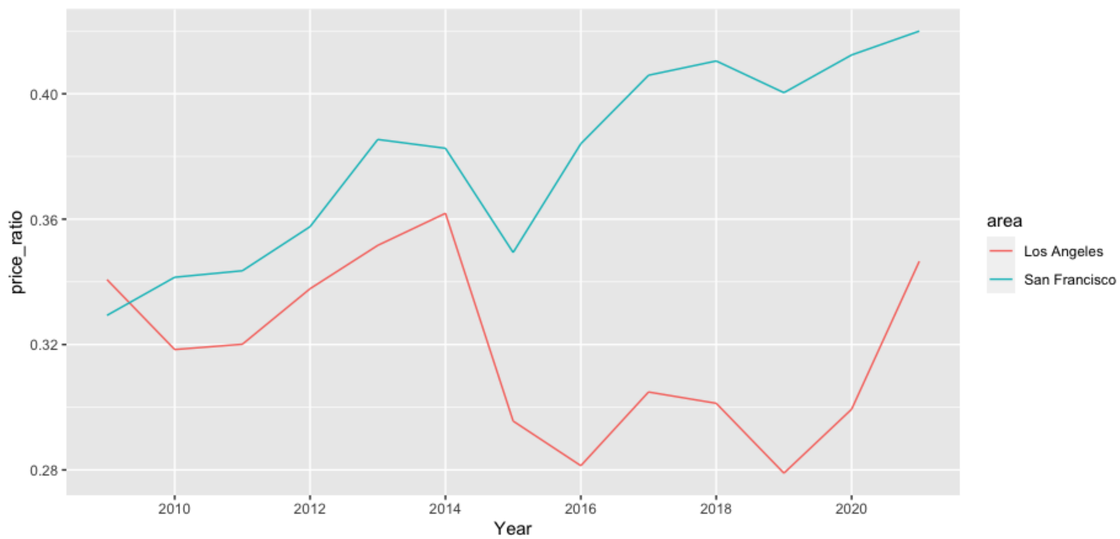

Figure 5: Price ratio over time by area

	SCE		PGE	
	mean	sd	mean	sd
Electricity Prices (cent/kWh)	16.147	1.039	19.411	2.910
Gasoline Prices (cent/gal)	373.581	28.496	374.227	31.351
EV cent per mile	5.329	0.343	6.406	0.960
ICEV cent per mile	16.811	.282	16.840	1.411
Price Ratio	0.318	0.026	0.379	0.030

Table 2: Energy Prices Data Set - Summary Statistics

3.3 Dataset Considerations

The electricity prices data set is very representative of the entire population – that is all the zip codes powered by SCE, PG&E, and SDG&E – as only few zip codes that represented outliers in the data were dropped. The energy prices data set drops all zip codes powered by SDG&E as it does not include gasoline price data in the San Diego area. However, if we consider the new population as the zip codes in the SCE and PG&E domain only, the data set is still representative of the overall population.

Although representative of the overall population, there are many ways in which my data set could have been improved. First, a better data set would contain more granular data such as EV registration at the block census group and monthly level, as well as monthly electricity and gasoline prices rather than annual averages only, like is the case in Bushnell et al. (2022). That way, I would be able to conduct a more precise analysis. Second, by including gasoline prices for the San Diego area in the energy price data set, data points would not be dropped and the analysis would consider the zip codes in all the three utilities' domain. Finally, by accounting for the annual income data by zip code rather than the median income by zip code in 2021, the analysis would account for non-constant growth in income that is not captured by the fixed effects model. I will expand more on this issue in the results section of this paper.

4 Methodology

To answer my research question I will employ a variety of fixed effect panel regression models. The dependent variable of all models is the cumulative sum of EV registration per capita multiplied by 10,000, and the unit of observation in the data is EV registration by zip code and by year. I am considering the running total – that is each year's EV registration is summed to the EV registration count of previous years in that zip code – to account for the growth of EVs over time and for the total contribution at any point in time. Additionally, I am considering EVs per capita to normalize the amount of EVs registered by the zip code's population. Finally, I multiply the EV registration variable by 10,000 to facilitate the results' interpretation, as not only it matches Bushnell et al.'s (2022) independent variable, but it also allows me to work with numbers that are bigger in magnitude. The main explanatory variables in the model are electricity prices, gasoline prices, and two binary variables for low and high income zip codes.

To answer the research question I will employ OLS regression models that build on regression 1, which represents the most basic model used to establish a baseline estimate of the impact that electricity prices have on EV adoption. In all regressions I control for the fixed effects of year and zip code. Controlling for fixed effects ensures that all the variables that could potentially have an effect on predicting the independent variable are accounted for as long as these variables or the rate at which they change remains constant over time.

4.1 Electricity Prices

$$BEVSalesPerCapita_{zt} = \beta_0 + \beta_1 Pe_{zt} + \eta t + \theta z + \mu \tag{1}$$

$$BEVSalesPerCapita_{zt} = \beta_0 + \beta_1 Pe_{zt} * LowIncome_z + \beta_2 Pe_{zt} * HighIncome_z + \eta t + \theta z + \mu \tag{2}$$

Regression 1 is the baseline model and its only explanatory variable is the price of electricity. Regression 2 builds on regression 1 as the low and high income binary variables are added to the model. The low income binary variable equals 1 for all the zip codes that have median households income below the mean, whereas the high income binary variable is defined as 1 for those zip codes with 2021 median household income above the mean. The two binary variables allow to differentiate the effect that electricity prices have on the two income groups' EV adoption. The expectation is that both coefficient have a negative sign, and that the coefficient for low income is characterized by a greater absolute value. This is because, as low income people are more elastic to changes in price, one would expect a one cent increase in electricity prices to affect EV registration in low income zip codes more negatively (Muehlegger and Rapson, 2021).

In order to estimate what the current EV adoption level would be if California IOUs were charging consumers efficient volumetric prices, I run a prediction model based on model 2. I establish the efficient electricity prices according to Borenstein et al., who find that they are equal to half of the current SCE prices and one third of current PG&E and SDG&E prices.

4.2 Gasoline Prices

I add gasoline prices to the model in order to prevent the results from being affected by omitted variable bias. I consider both electricity and gasoline prices variable in the cost in cent it takes to drive one additional mile. Therefore, the variables *BEV cent x mile* and *ICEV cent x mile* indicate the effect of a one cent increase in the cost to drive an additional mile with an EV and an ICEV respectively. The same unit of measure enables me to compare the coefficients in a meaningful way and to account for their relative effect through the *price ratio* variable.

$$BEVSalesPerCapita_{zt} = \beta_0 + \beta_1 BEVcentx1mile_{zt} + \beta_2 ICEVcentx1mile_{zt} + \eta t + \theta z + \mu \quad (3)$$

$$BEVSalesPerCapita_{zt} = \beta_0 + \beta_1 PriceRatio\eta t + \theta z + \mu \quad (4)$$

$$BEVSalesPerCapita_{zt} = \beta_0 + \beta_1 BEVcentx1mile_{zt} + \beta_2 PriceRatio\eta t + \theta z + \mu \quad (5)$$

In model 3, the cost to drive one additional mile in an EV and in an ICEV seek to explain the variation in EV sales linearly and separately. Model 4 looks at how the relative change of electricity and gasoline prices affects EV adoption through the *price ratio* variable, which is computed by dividing *BEV cent x mile* by *ICEV cent x mile*. The *price ratio* coefficient indicates the effect of a one cent increase in the ratio between the two energy prices. Looking at the change in prices as a proportion rather than linearly might be beneficial for the model's effectiveness, especially given the lack of variation in gasoline prices data. Model 5 is an iteration of models 3 and 4 as it brings together the linear and relative models, and it looks at how effective a combination of the two previous models is at explaining the variation in EV adoption. In general, I expect the *BEV cent x mile* and *price ratio* coefficients to be negative, and the *ICEV cent x mile* coefficient to be positive, coherently with what Bushnell et al. (2022) finds.

$$\begin{aligned} BEVSalesPerCapita_{zt} &= \beta_0 + \beta_1 BEVcentx1mile_{zt} * LowIncome_z + \\ &+ \beta_2 BEVcentx1mile_{zt} * HighIncome_z + \beta_3 ICEVcentx1mile_{zt} * LowIncome_z + \\ &+ \beta_4 ICEVcentx1mile_{zt} * HighIncome_z + \eta t + \theta z + \mu \qquad (6) \end{aligned}$$

$$\begin{aligned} BEVSalesPerCapita_{zt} &= \beta_0 + \beta_1 PriceRatio * LowIncome_z + \\ &+ \beta_2 PriceRatio * HighIncome_z + \eta t + \theta z + \mu \qquad (7) \end{aligned}$$

$$BEVSalesPerCapita_{zt} = \beta_0 + \beta_1 BEVcentx1mile_{zt} * LowIncome_z +$$
$$+ \beta_2 BEVcentx1mile_{zt} * HighIncome_z + \beta_3 PriceRatio * LowIncome_z +$$
$$+ \beta_4 PriceRatio * HighIncome_z + \eta t + \theta z + \mu \quad (8)$$

Models 6 through 8 build on models 3 to 5 by interacting each previous models' variables with both the high and low income binary variables. The interaction terms allow to quantify how energy prices affect the two income groups' EV adoption differently.

Additionally, similarly to model 2, I predict the EV adoption level in 2021 under efficient retail pricing by running a prediction of model 7, which I expect to be the best at explaining EV adoption variation. To run the prediction model I once again divided the electricity prices in the LA area, that is SCE prices, by 2 and electricity prices in the SF area, that is PG&E prices, by 3. After recomputing the *BEV cent x mile* and the *price ratio* under efficient pricing, I estimate the predicted level of EV adoption.

$$BEVSalesPerCapita_{ct} = \beta^e P^e_{ct} + \beta^g P^g_{ct} + \eta_c + \theta_t + \mu_{ct} \quad (9)$$

The models in this study are inspired from and build on model 9, employed by Bushnell et al. (2022). Therefore, the expectation is that the results of this paper's model align with those of regression 9, that is the EV related price coefficient should be negative and the ICEV related price coefficients should be positive. On top of that, like previously explained, I expect the magnitude of the low income coefficients to be bigger.

Although this paper and its models are inspired by Bushnell et al.'s model, there are some important differences between the two studies that is worth pointing out as they could be the cause of differing results. First, the units of observations in (Bushnell et al., 2022) are more granular. In fact, the spatial unit of the paper is census block group which is a geographical unit smaller than zip code. In addition, the authors estimate a version of regression 9 at both the monthly and annual level, getting therefore more specific results. A third difference is that Bushnell et al. do not include an income variable, and therefore look at the effect that energy prices have on EV adoption for the overall population. On the other hand, models 6 through 8 all distinguish between the effect on households characterized as low and high income.

5 Results

5.1 Electricity Prices

Table 3 shows the results of regressions 1 and 2. Regression 1's coefficients appear to be significant only when neither the fixed effect of year and zip code are accounted for, therefore not allowing to draw any meaningful conclusion about the relationship between EV adoption and electricity prices that accounts for difference among years and zip codes. In regression 2, where the low and high income binary variables are introduced as interaction terms with electricity prices, the coefficients become statistically significant at the 99% confidence level when the fixed effect of both year and zip code are accounted for. Additionally, the R^2 increases from 60 to 70, indicating that introducing the income variable in the regression betters the model as the independent variables now explain a higher share of the variance of EV sales per capita.

With regard to the direction of the relationship between EV adoption and electricity prices in model 2, it appears that electricity prices are negatively correlated with EV adoption for low income households and positively correlated with EV adoption for high income ones.

The results can be interpret as follows: a one cent increase in electricity prices leads to 12.26 more high income households and 10 less low income households purchasing an EV.

The relationship between electricity prices and EV adoption in low income zip codes is as expected, and so is the comparison between high and low income zip codes as a one cent increase in electricity prices affects low income households more negatively. However, the positive coefficient for high income consumers suggests that the demand curve for high income households is upward sloping, which cannot be the case. In fact, there must be omitted variable bias in the model that results in an overestimation of the coefficient. I will thoroughly discuss this issue later in the results section.

Dependent Variable:	BEV registration					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	-153.5***			-149.1***		
	(4.023)			(3.695)		
price	10.36***	0.1423	-0.4596			
	(0.2125)	(0.1805)	(0.3674)			
price × low income				8.671***	-1.879**	-9.966***
				(0.1977)	(0.6220)	(1.730)
price × high income				12.07***	1.602***	12.26***
				(0.1977)	(0.4450)	(1.757)
Fixed-effects						
year		Yes	Yes		Yes	Yes
zip_code			Yes			Yes
Fit statistics						
Observations	15,353	15,353	15,353	15,353	15,353	15,353
R^2	0.13409	0.27768	0.60116	0.26986	0.41999	0.70438
Within R^2		1.65×10^{-5}	0.00010		0.19702	0.25888

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3

As discussed in the literature review, California's IOUs recover their total system costs by charging high volumetric prices that deceive consumers about the true cost of consuming electricity as prices greatly exceed social marginal cost. I run a prediction model to estimate the extent to which inefficient electricity prices hinder EV adoption for each income group. Figure 6 shows that the amount of EVs registered from 2009 to 2021 would have been consistently and increasingly higher among low income households for all IOUs if retail electricity prices equaled social marginal cost. Table 4 shows the actual and the predicted means of EVs registered under efficient pricing by utility in 2021. The difference between means is also displayed and it shows that there would be on average 126 more EVs in each low-income zip codes powered by SCE, 187 more in low-income zip codes powered by PG&E, and 178 additional EVs in zip codes powered by SDG&E. The weighted average indicates that there would be a total of about 167 additional EVs every 10,000 households in each zip code characterized as low income across the three IOUs territories. On the other hand, the difference between predicted and actual EV adoption in zip codes characterized as high income is negative for all three IOUs, and the growth over time would have been consistently lower under efficient pricing for high income households, as shown in figure 10 in the appendix. These results are coherent with the negative of sign of the β_3 coefficient in model 2.

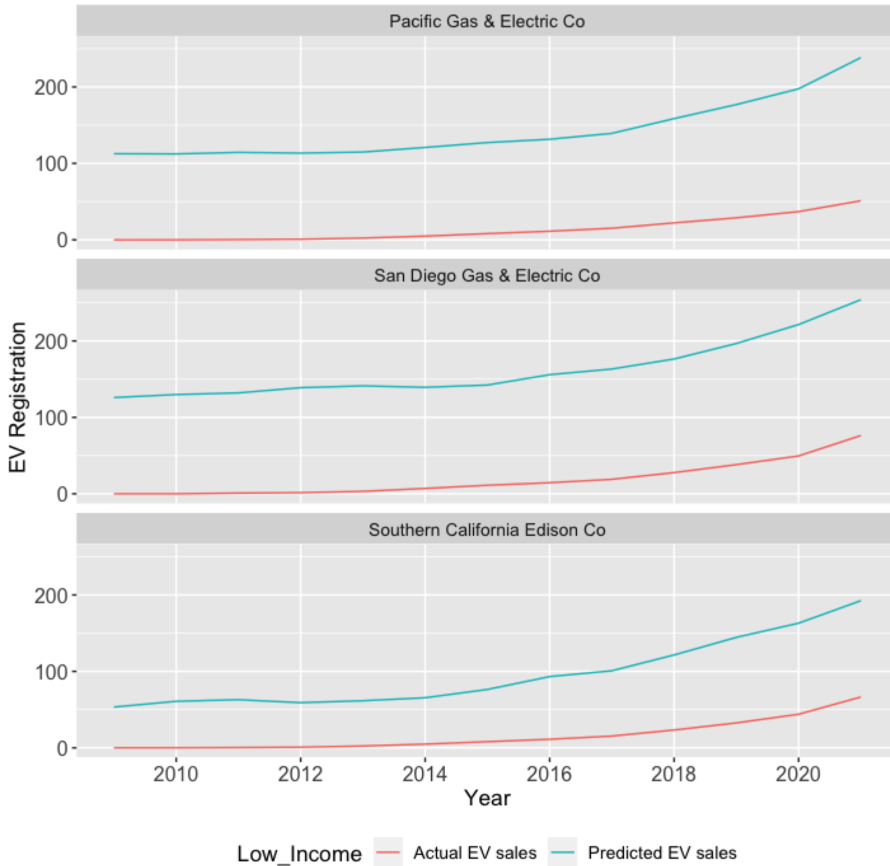

Figure 6: Low Income Consumers' Predicted EV Adoption Under Efficient Pricing vs Actual

	ACTUAL			PREDICTED			DIFFERENCE (P-A)		
	Low Income	High Income	Overall	Low Income	High Income	Overall	Low Income	High Income	Overall
SCE	66.5	282.7	160.7	192.5	100.3	152.3	126	-182.4	-8.4
PG&E	51.1	265.5	135.7	238.4	43.3	161.4	187.3	-222.2	25.7
SDG&E	76.2	267.4	193.4	254	25.9	114.1	177.8	-241.5	-79.3

*EV sales: cumulative sum for 10,000 households

Table 4: Mean EV Registration in 2021: Actual vs Predicted

5.2 Introducing Gasoline Prices

Table 5 shows the results of models 3 through 8 in order. The R^2 is around 0.60 for the models in which the income variables are not included, and it increases to 0.70 when the income binary variables are included, although it only increases to 0.63 for regression 7. Overall, it looks like adding the gasoline price variable does not increase the share of the dependent's variable variance explained by the independent variables with respect to when only electricity prices are considered.

The coefficients of models 3 and 6 are shown in columns 1 and 4 of table 5. Whereas the coefficients of model 3 appear statistically insignificant, model's 6 β_2 and β_3 coefficients are significant at the 95% confidence level and can be interpreted as follows: as it becomes one cent more expensive to drive one additional mile in an EV, 23.36 more high income households will purchase one, and as driving one mile in a gasoline-powered car becomes one cent more expensive, 22 fewer high income households will purchase an EV each year. The direction of the relationship between the cost of driving an EV and an ICEV and EV adoption is opposite to what I expected and to what previous literature found. In fact, the authors of *Energy Prices and Electric Vehicle Adoption* find that an increase in one cent per kWh results in a drop of annual EV sales of about 0.6%, and a one cent increase per gallon of gasoline increases EV registration by about 1.5% (Bushnell et al., 2022). Although I differentiate for income levels, I would expect the direction of the relationship to be coherent with Bushnell et al. (2022)'s results and to potentially only differ in magnitude, with low income consumers' showing bigger magnitudes of their coefficients. Because of inconsistency with expectations and previous research, I conclude that models 3 and 6 fail at explaining the variation in EV adoption, probably due to their linearity which is not ideal given the lack in gasoline price variation in the data.

Columns 3 and 6 show the coefficients of models 5 and 8, which mix linear and proportional explanatory variables in an attempt to explain the variation in EV adoption. Both models' β_1 coefficients are statistically significant and negative, and can be interpreted as follows: as the cost to drive one mile with an EV increases by one cent, 32.5 less consumers will purchase one and 70.9 fewer low income consumers will purchase an EV. However, the positive *price ratio* coefficient that characterizes both regressions indicates that, as it becomes more expensive to drive an EV with respect to an ICEV, more overall consumers and low income consumers respectively will purchase an EV. Therefore, combining linear and proportional explanatory variables also fails to properly describe EV adoption in a way that is coherent with the expectations and with previous literature.

Models 4 and 7, which fully disregard the linear model and consider the price ratio as the only explanatory variable, appear to be the best models at explaining the variation in EV adoption. In fact, regression 4's results indicated that, as it becomes relatively more expensive to drive one additional mile in an EV with respect to an ICEV, about 46 fewer consumers will purchase an EV. When the income variables are also included in the model, the relationship between the price ratio and EV adoption remains negative for low income zip codes but it becomes positive for high income ones. More specifically, as the cost to drive an EV with respect to an ICEV increases by one cent, 550 more low income and 670 more high income households will purchase an EV. Similarly to the results of model 2, the relationship between low income households' EV adoption and energy prices is as expected, but that between high income people's EV adoption and electricity prices seems to be guided by an upward sloping demand curve which cannot be the case in real life. Therefore, the high income coefficient must be disregarded since it must be influenced by other variables not captured in the model.

Dependent Variable:	BEV registration					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
BEV_centxmile	-0.4232		-32.54**			
	(1.279)		(13.75)			
ICEV_centxmile	-12.35					
	(7.025)					
price_ratio		-46.23*	592.4**			
		(24.72)	(263.3)			
BEV_centxmile × low_income				-13.70		-70.85***
				(7.819)		(15.73)
BEV_centxmile × high_income				23.36**		31.93***
				(10.50)		(8.763)
ICEV_centxmile × low_income				-22.12**		
				(7.825)		
high_income × ICEV_centxmile				1.564		
				(6.038)		
low_income × price_ratio					-550.3**	1,033.2***
					(210.1)	(263.4)
high_income × price_ratio					670.1**	-139.6
					(267.0)	(325.8)
Fixed-effects						
year	Yes	Yes	Yes	Yes	Yes	Yes
zip_code	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	13,975	13,975	13,975	13,975	13,975	13,975
R^2	0.59470	0.59413	0.59482	0.70979	0.63389	0.70996
Within R^2	0.00169	0.00028	0.00198	0.28517	0.09821	0.28559

Clustered (year) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5

I run a prediction model based on regression 7 to estimate the current EV adoption level when accounting for gasoline prices. Figure 8 shows the actual and the predicted growth in EV registration by area. For both Los Angeles and San Francisco areas, the mean of predicted EV registration over time is consistently and considerably higher under efficient retail pricing, with the gap between actual and predicted EV sales increasing with time and peaking in 2021. Table 6 shows the actual and mean EV registration levels by area in 2021. If IOUs charged efficient prices, in LA and SF there would currently be an average of 136 and 201 more EVs in each low income zip codes respectively. By computing the weighted average, the result indicates that there would currently be on average 181 additional EVs registered in all zip codes characterized as low income.

With regard to high income zip codes, the model actually predicts that there would be less, and at times negative, EV adoption over time, like shown in graph 12 in the appendix. This is coherent with the positive β_2 coefficient of regression 7 and is similar to the EV registration prediction in high income zip codes of model 2.

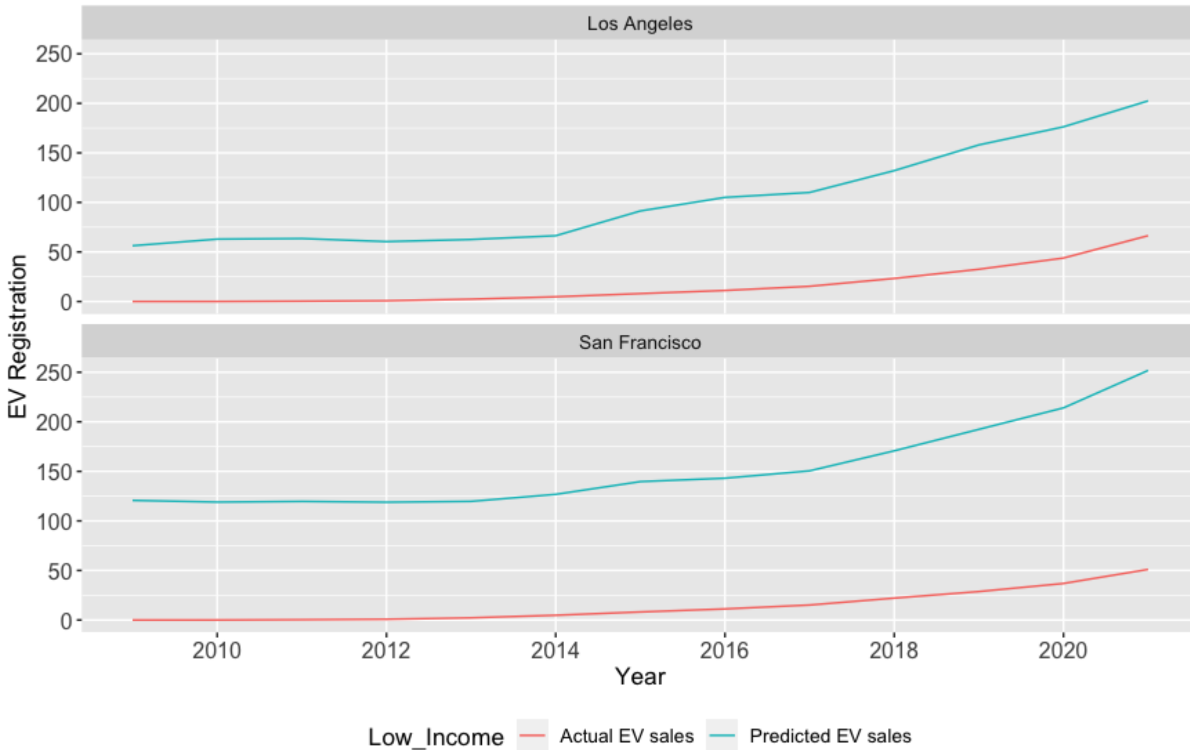

Figure 7: Low Income Consumers' Predicted EV Adoption Under Efficient Pricing vs Actual

	ACTUAL			PREDICTED			DIFFERENCE (P-A)		
	Low Income	High Income	Overall	Low Income	High Income	Overall	Low Income	High Income	Overall
Los Angeles	66.5	282.7	160.7	202.5	82.5	150.2	136	-200.2	-10.5
San Francisco	51.1	265.5	135.7	251.9	21.9	161.1	200.8	-243.6	25.4

Table 6: Mean EV Registration in 2021: Actual vs Predicted

5.3 Discussion

The main limitation of this study is its inability to draw conclusions with regard to the relationship between EV adoption and electricity prices in zip codes characterized as high income. In fact, the relationship looks like it is driven by an upward sloping demand curve, which in general would indicate that as a good becomes more expensive, consumers will purchase more of it. An upward sloping demand curve cannot be the case in real life as it goes against the negative relationship between price and demand, one of the main principles of economics. A probable reason why both parts of the study show this positive relationship is the presence of omitted variable bias in the data. Although controlling for the fixed effects of year and zip code should account for the variables not included in the model that could have an effect on EV adoption, this is only the case if these variables do not change over time or change at a constant rate. However, if variables that have an effect on EV adoption change at a varying rate over time, the fixed effects will not account for them. I suspect this to be exactly what is going on in the data, as the relatively low R^2 — which in none of the models exceeds 0.70 – also indicates that key variables are missing.

An example of a variable of which effect is not captured by the models is variation of income. In fact, if rich regions are becoming increasingly wealthier over time, consumers in these regions will gain higher disposable income and as a consequence they will be willing to purchase an EV regardless of the increasing electricity prices. As the increase is likely to not be constant among regions, by only accounting for one income observation – the median household income in 2021 – the income growth effect is not captured and its effect on EV adoption is mistakenly attributed to electricity prices. A way that this could have been prevented is by collecting data on median household income at the annual level. Additionally, in areas that are getting richer and in which consumers are purchasing EVs at an increasing rate, this effect could be further amplified by the network effect. Essentially, as more people in the vicinity of a consumer purchase an EV, that consumer's utility from owning one will also increase.

Technology improvements is another variable that could be relevant to explain EV adoption, especially among high income households. In fact, these consumers could value EVs more over time because of technological improvements such as a longer driving range and a quicker charging time that make EVs a more valuable good. As a consequence, consumers would be willing to purchase one regardless of the electricity prices getting more expensive, as the overall utility they gain from owning an EV has increased. Similarly to income, by not including such variable in the data, the regressions' results will attribute the higher EV adoption rate to electricity prices, leading to an over-estimation of the electricity price coefficient. The technology improvements lurking variable would be mostly relevant for high income consumers because as they are less price elastic than low income ones, and are therefore likely to place greater value on non-monetary factors such as EV quality (Muehlegger and Rapson, 2021).

Finally, A further limitation of the study is represented by the gasoline prices which show close-to-zero variation among the San Francisco and Los Angeles areas in any given year. Since there is such little variation, it is complicated to estimate the effect of gasoline prices on EV adoption among the two regions considered, and it is in fact not surprising that the direction of the relationship between the two income groups' EV adoption does not change when gasoline prices are introduced in the model. The root of this issue stands in approximating the gasoline prices. SF and LA have similar gasoline prices, which are then reflected on the entirety of the areas covered by PG&E and SCE. Since PG&E and SCE extend beyond the two cities of SF and LA, it results in very similar prices among the entire population considered. This could have been improved if more spatially granular gasoline prices, ideally at the zip code level, were available.

specify that values are multiplied by 10,000 in summary tables

6 Conclusion

In this paper I investigate how the inefficiently high electricity prices charged by the three major IOUs in California affect EV adoption differently among zip codes characterized as low and high incomes. A main goal of my research is to quantify what the current EV registration level would be among each income group if electricity prices equaled social marginal cost. The existing literature agrees on the negative relationship between electricity prices and EV adoption (Bushnell et al., 2022). Additionally, low income consumers have been defined as more price elastic in the electricity market (Muehlegger and Rapson, 2021). Therefore, when differentiating among income groups, the expectation is for such relationships to stay negative for both income levels, and low income consumers' coefficient is expected to be bigger in magnitude.

I conduct various panel fixed effect regression models, first considering electricity prices only, and then adding gasoline prices to the model as well. As expected, the results show a strong and negative relationship between electricity prices and EV adoption in low income zip codes. Additionally, the coefficient for low income zip codes does in fact appear to be consistently and significantly smaller than that of high income zip codes. However, the study fails to quantify the extent to which low income households are more adversely affected, as the coefficient for high income zip codes appears to be consistently positive. A positive coefficient implies the existence of an upward sloping demand curve and therefore the results relative to high income consumers are deemed inconclusive.

Although the results of this paper are partially inconclusive, the study is still relevant as it finds that current EV registration levels would be significantly higher under efficient retail electricity pricing in low income zip codes. This is significant because it shows that setting electricity prices above social marginal cost greatly slows down the electrification of the transportation sector. Additionally, the positive coefficient for high income households indicates the presence of uncontrolled lurking variables in the model, such as income growth and technological progress, which are affecting high income consumers' decision to purchase an EV. This shows that low income consumers do in fact place more weight on electricity prices than their high income counter parts, and that the high electricity prices represent an inequality concern in the California EV market.

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Appendices

Table 5 shows the calculations I computed to find how many years it takes to make up for the higher up front cost of an EV. I found the average price of an EV and an ICEV on Kelley Blue Book, and I subtracted the minimum federal EV tax credit amount of $2,500 to obtain an average EV purchase price of $49,032. I assumed that the average California driver travel 12,524 miles per year (Meyer, 2023) and I found that the average fuel needed to drive one mile in an EV is 0.33kWh (Eco Cost Savings, 2022) and in an ICEV it is 0.045 gallons (Idaho National Laboratory, n.d.). The average fuel prices are for the year 2021. I calculated the average price of electricity by averaging the prices the three main IOUs charged in 2021 according to my data, and I retrieved the price of gasoline in 2021 in California from the US Energy Information Administration (2023). Given that the cost to own a car is the addition between the purchase price of the car and the yearly cost to fuel it, which can be found by multiplying the average miles driven in a year by the fuel necessary per mile and the fuel price, I calculated that it costs on average $1,302.8 more to power a conventional car compared to an EV. By dividing the difference in up front price by the difference in the cost to drive the two vehicles over a year, I calculate that it takes 6.7 years to make up for the upfront cost of an EV.

	Price of car	Miles x year	Fuel x 1 mile	Fuel price	Price of fuel x year	cost to own
ICEV	$40,326	12,524 miles	0.045 gal	$4.013 gal	$2,261.65	$42,588
EV	$49,032	12,524 miles	0.33kWh	$0.232 kWh	$958.84	$49,991

Table 7: Cost to own: EV vs. ICEV under actual electricity pricing

When considering efficient electricity pricing, that is by diving SCE prices by 2 and

PG&E and SDG&E by 3, the efficient electricity prices can be computed (Borenstein et al., 2021). When considering the efficient prices it now costs \$1898.5 more to power an ICEV every year, and it takes consumers 4.6 years to make up for the upfront cost of an EV.

	Price of car	Miles x year	Fuel x 1 mile	Fuel price	Price of fuel x year	cost to own
EV	\$ 49,032	12,524 miles	0.33 kWh	0.0879 kWh	\$ 363.134	\$ 49,395

Table 8: Cost to own: EV vs. ICEV under efficient electricity pricing

The areas in blue are pricing above SMC, while the areas in red are pricing below SMC.

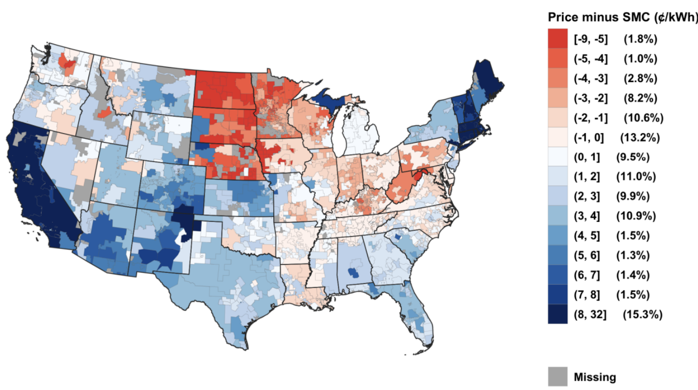

Figure 8: (Borenstein and Bushnell, 2021) Marginal Price minus Average Social Marginal Cost per kWh, considering SCC equal to \$50/ton

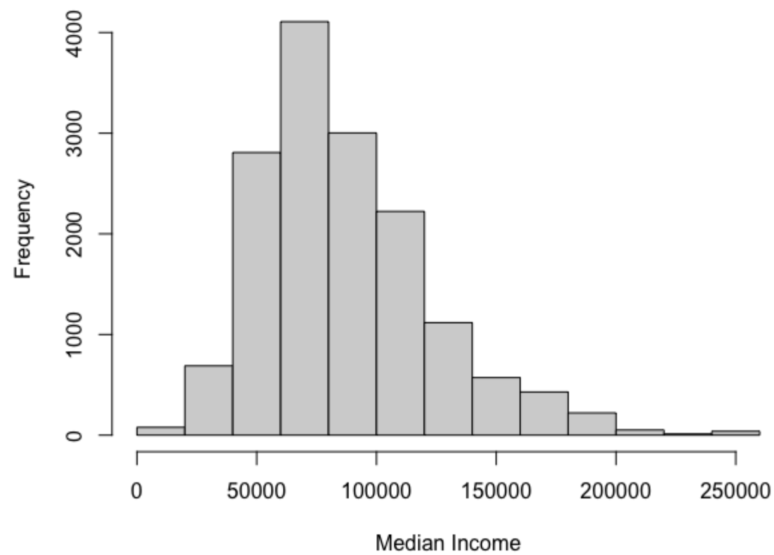

Figure 9: Income Distribution

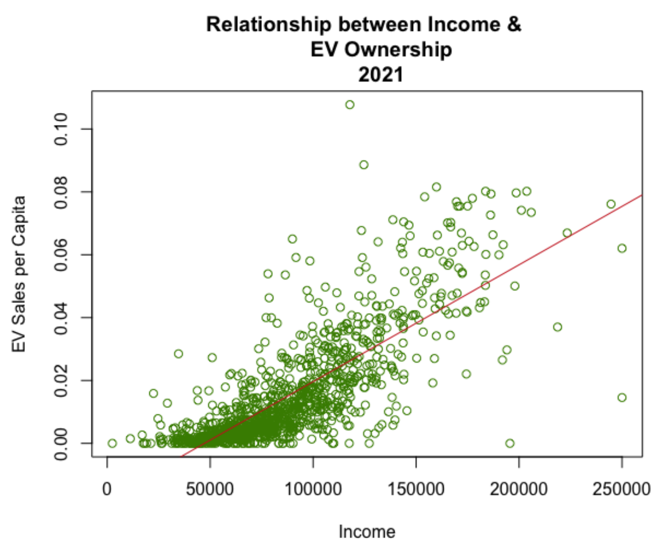

Figure 10: EV sales per capita over time

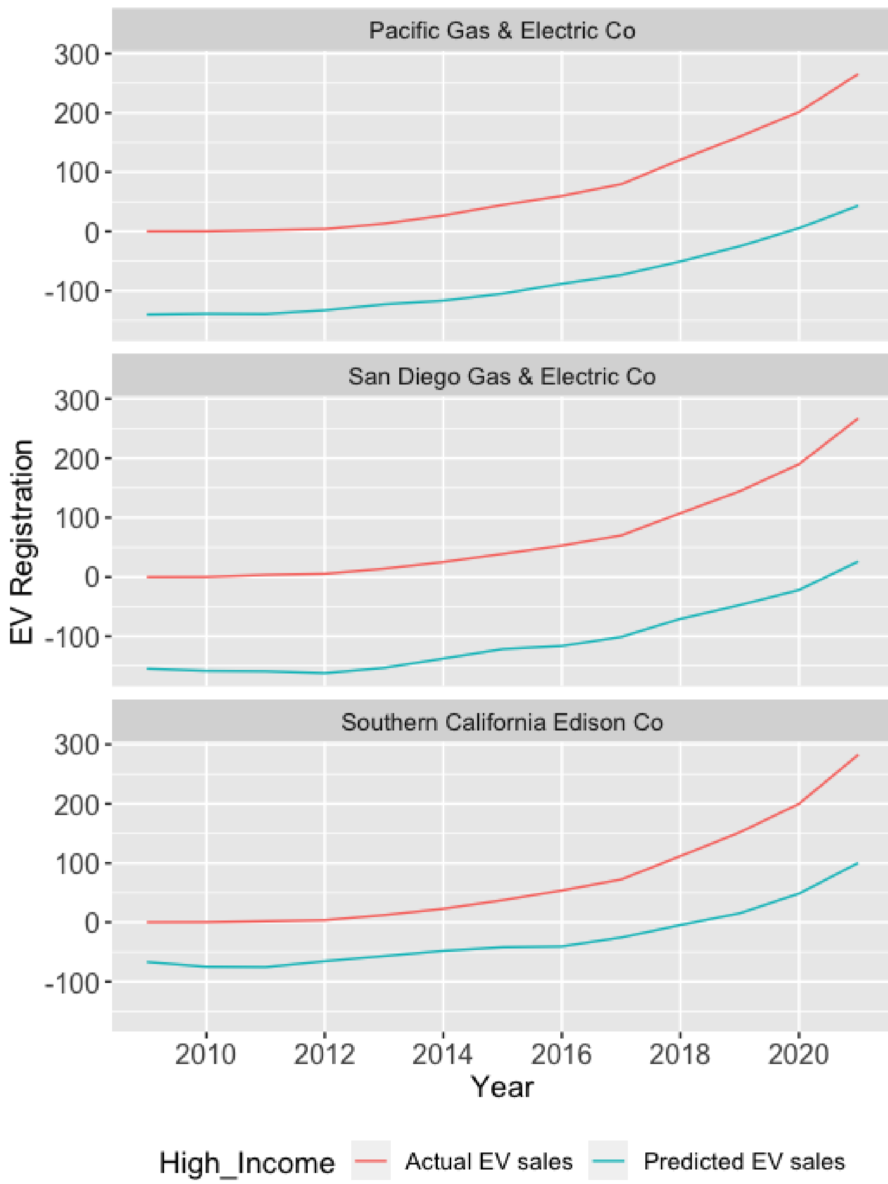

Figure 11: High Income Consumers' Predicted EV Adoption Under Efficient Pricing vs Actual - electricity prices

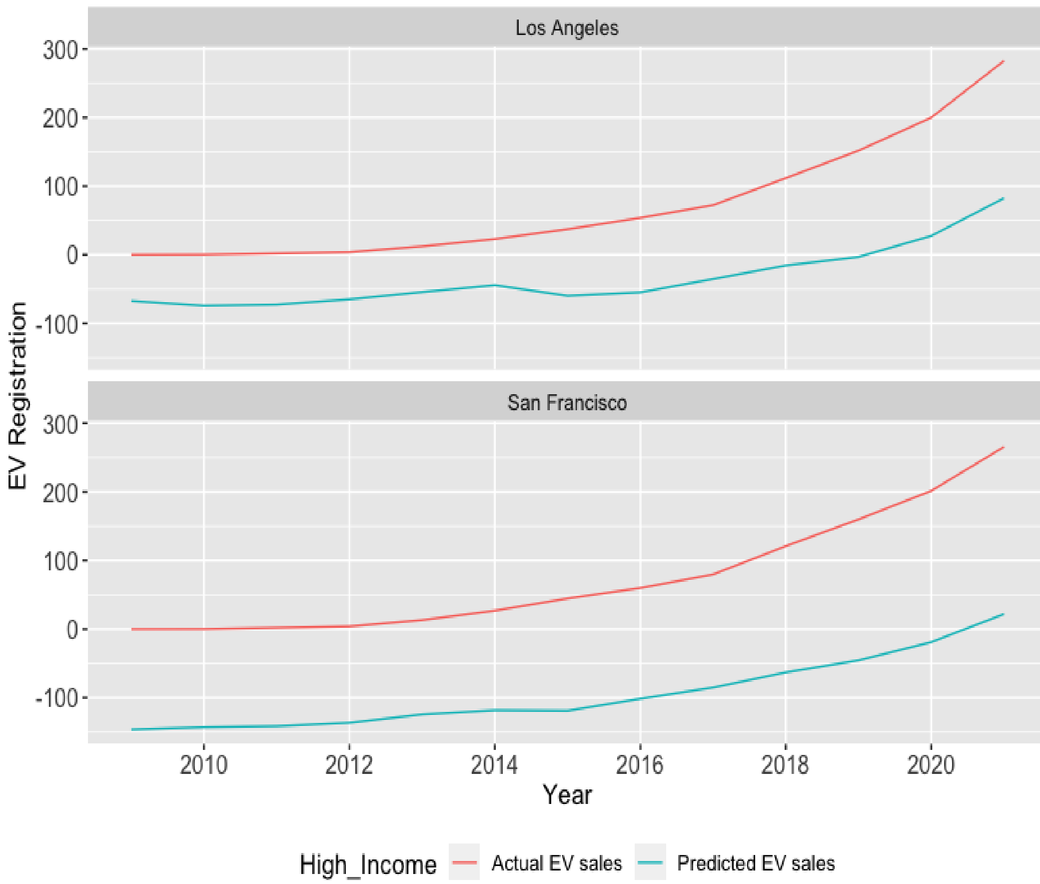

Figure 12: High Income Consumers' Predicted EV Adoption Under Efficient Pricing vs Actual - energy prices