THREE ESSAYS ON ELECTRIC VEHICLE ADOPTION, ITS EFFECTS, AND RELATED INCENTIVES

by

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of

Doctor of Economics

Middle Tennessee State University

August 2021

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To my Mother, who taught me to dream big.

To my Husband, who never let me quit my dream.

To Professor Anu Muhammad, who gave me the courage to chase my dream.

ACKNOWLEDGEMENT

I owe a debt of gratitude to lots of people who helped me complete this journey. I am blessed to have a wonderful committee who brought the best out of me. I want to thank my supervisor, Dr. Roach, for his relentless guidance and support. I am solely indebted to those countless numbers of meetings, zoom meetings, and email feedbacks you have given me in the past two years. I want to thank Dr. Rennhoff for your uncompromising, honest directions, Dr. Gamble for your timely nudge and support. Also, thank you, Dr. Eff, for all the help and guidance you have given me whenever I asked. I could complete my work smoothly even in this global pandemic only because you all had got my back.
I am grateful to the Department of Economics. I have been taught by outstanding, talented professors, and also at the same time, I learned a lot from my cohorts and other students. This graduate study was once in a lifetime journey.
I want to extend my gratitude to my family members, both my own family and my in-laws. I could not be what I am today without your love, support, and invaluable sacrifice. This is beyond my capability to express how thankful I am to all of you for enabling me to have this experience.

ABSTRACT

This dissertation thesis explores few aspects of electric vehicle (EV) adoption; more specifically, this study focuses on the incentive policies on EV, the effects of EV adoption on energy consumption, and the factors behind the joint adoption of EV and solar Photovoltaics (PV). In the first chapter of my dissertation, I analyze the effect of state-level tax credit policy on electric vehicle sales in Maryland by focusing on a synthetic control approach using Bayesian structural time series. I found this incentive indeed increased the electric vehicle (EV) adoption, but at the same time, the State's goal of EV adoption is too high to achieve with the current incentive program. As I have observed a substantial increase in EV adoption by the State incentive program, I elaborate my analysis on my second chapter, which focuses on two different but interrelated aspects of EV adoption. First, using California's monthly county-level data for 2010 to 2019, this study reveals that EV, and their supportive infrastructures significantly increase residential and commercial electricity consumption. Second, analyzing the electricity generation information by county, this study concludes that there is a significant negative relation between EV adoption and the share of electricity from renewable sources. This study argues that unless California adopts cleaner sources of power plants, public spending on EV adoption may not result in a clean atmosphere, which was the primary concern of the EV incentive policies in the first place. That leads me to my third chapter, which explores the factors behind the joint adoption of EV and solar PV, as solar PV is an environmentally friendly energy generation option for households. I find education levels significantly influence the future decision of the joint contribution. Also, income level and household type are essential factors of adoption.

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CHAPTER I

THE EFFECT OF TAX CREDIT POLICY ON ELECTRIC VEHICLE SALES: A SYNTHETIC CONTROL APPROACH USING BAYESIAN STRUCTURAL TIME SERIES

An electric vehicle is becoming an important transportation choice day by day, mostly because of its energy efficiency. Recently, many countries have set goals to ban the sales of gasoline and diesel-powered vehicles in the future to reduce greenhouse gas emissions; notably, Norway by 2025, China by 2030, India by 2030, Germany by 2030, France by 2040, and Britain by 2040 or 2050 (Fingas, 2016; Petroff, 2017; Riley, 2017). Similarly, many cities around the world have begun transitioning public transportation towards environment-friendly electric vehicles (Forrest, 2017).

An electric vehicle (EV) or electric car is an automobile that is propelled by one or more electric motors, using energy stored in rechargeable batteries.

Until December 2018, there were about 5.3 million light-duty all-electric and plug-in hybrid vehicles in use across various countries in the world. Most recently, in July 2019, US-based Motor Trend Automotive Magazine awarded an electric car as the "ultimate car of the year" (Guarnieri, 2012). Compared with internal combustion engine cars, electric vehicles are quieter, have no tailpipe emissions, and have lower emissions in general.

Several national and local governments have established government incentives, like tax credits, subsidies, etc., for plug-in hybrids and electric vehicles. The aim is to promote the introduction and adoption in the mass market of new electric vehicles, generally depending on battery size, their electric range, and purchase price. The current maximum tax credit allowed by the US Government is US $7,500 per car (Alternative Fuel Data Center [AFDC], 2019). Prior studies have tested these policy effects with various discrete choice models. As a better alternative to estimate the tax incentive effects on consumer purchases, this study employs the Bayesian structural forecasting model.

The rest of this study is organized as follows. First, I give a brief literature review in section 2. In section 3, I present an overview of data and Maryland tax credit policy. Section 4 discusses the theoretical background and model specification. I present the result of my analysis in section 5. Finally, I include robustness checking and sensitivity analysis in section 6 before concluding in section 7, with discussions about the limitation and scope of this study.

Literature Review

Østli, et al., (2017) found that purchase tax for vehicles of higher CO_2 emission with exemptions granted for battery electric vehicles has a major impact on the average type of approval rate of CO_2 emissions from new passenger cars registered in Norway. The fuel tax in Norway also encourages car customers to buy low emission vehicles. In contrast, Liu and Cirillo (2017) proposed a dynamic discrete choice model for Maryland car consumers and forecasted a decrease in both hybrid and electric car adoption. This paper formalizes a general dynamic discrete choice framework in which forward-looking agents optimize their utility over time; two options are available to consumers at each time: keeping the current vehicle or buying a new vehicle among the options available in the market. Concerning the behavior derived from the analysis, the authors suggested a conclusion that consumers are more interested in purchasing gasoline and hybrid cars, for which the predicted market shares a peak of around 20% over the nine-year study period. Electric cars represent 4-7% of the future market, and there is a slightly increasing trend over time. The market share of electric cars highly depends on electricity price, purchasing price of the electric car, MPG equivalent electricity, and recharging range. The data used for this analysis were collected from a self-interview and web-based stated preference survey, which was designed to analyze households' future preferences on new vehicle adoption in a dynamic market. Moreover, a new method to solve multivariate discrete-continuous problems is introduced by Fang (2008). He develops and applies the model to measure how much residential density influences households' vehicle choices. He proposes a more flexible method of modeling vehicle holdings in terms of the number of vehicles in each category, using a Bayesian multivariate ordinal response system. Using the 2001 National Household Travel Survey data, he finds that increasing residential density reduces households' truck holdings and utilization in a statistically significant but economically insignificant way. Nevertheless, Bolduc, et al., (2008) used a hybrid choice model to analyze the car choice pattern of Canadian consumers with new technology. They used perception and attitude as the latent variable of this hybrid model. With a multinomial logit model, they described the choice. The contribution of a given observation of the likelihood function of the full system is an intel of dimension equal to the number of latent variables in the model. All these above studies focused on several discrete choice models.

However, BSTS was first proposed by Scott and Varian (2013) and then extended to the synthetic control setting by Brodersen, et al. (2015). The article titled "Inferring causal Impact using Bayesian structural time series mode," discusses the strengths and limitations of the state-space model. This paper proposes to infer causal impact based on a diffusion-regression state-space model that predicts the counterfactual market response in a synthetic control that would have occurred had no intervention taken place. This forecasting method has the advantage that it does not require a set of control units and instead can use any related time series to predict the counterfactual. This synthetic control approach using the Bayesian structural model is used by Kurtz et al. (2019) to estimate the effect of Bariatric surgery on health care costs in the absence of a randomized control trial.

Overviews of Policy & Data

Maryland Tax Credit Program

In addition to federal incentives, Maryland is also offering a one-time excise tax credit of up to $3000 for qualified vehicles, which is effective from July 1, 2017, through June 30, 2020.

According to the House bill, qualified Plug-in Electric Vehicle (PEV) and fuel cell EV purchasers may apply for a tax credit against the imposed excise tax up to $3,000. The tax credit is first-come, first-served, and is limited to one vehicle per individual and ten vehicles per business entity. Vehicles must be registered in Maryland unless the vehicle manufacturer conforms to applicable state or federal laws or regulations governing PEVs or fuel cell EVs during the year in which the vehicle was purchased, or the vehicle was originally registered in another state (AFDC, 2019). A qualified vehicle must meet the following criteria:

a) Have a total purchase price not exceeding $63,000; (was $60,000 in 2017)

b) Be propelled to a significant extent by an electric motor that draws electricity from a battery with a capacity of at least five kilowatt-hours.

c) Have not been modified from original manufacturer specifications.

d) Be purchased and titled for the first time between July 1, 2017, and July 1, 2020.

e) The vehicle must have been acquired for use or lease by the taxpayer and not for resale.

f) There is no fee for applying for the tax credit.

The credit is returned to the taxpayer in the form of a check from the state. The state registration requires proof of residency, and an out-of-state permit does not require registration, and reselling the credit is not possible. Moreover, examining other applicable state's policies, it is clear that Maryland tax credit is not higher than other applicable States (AFDC, 2019). So, we can ignore the possibility that people from other states might be buying cars in Maryland or consumers from other applicable states might be applying for the tax credit in Maryland, which would cause the effect of the policy to be larger.

Another important thing is differentiating the pre and post-period of the policy, or in other words, the cut. Another important thing is differentiating the pre and post period of the policy, or in other words, the cut point of this model. This policy was effective from July 2017, but the bill of the excise tax credit for EV passed the Maryland House of Delegates on March 20, 2017, and then moved to the Senate for consideration, and this is the time the people of Maryland first came to know about the policy (Reference House Bill 1246, 2019). Also, as from the Maryland Department of Transportation Motor Vehicle Administration website, I came to know that titling and registering one's vehicle needs some additional time after purchasing. Maryland dealers are required by law to submit EV customers' title application documents and related fees no later than thirty days after the vehicle is delivered to the customer. Also, for registration, vehicles must be inspected by a licensed Maryland inspection station. A certificate of inspection is issued within ninety days of the vehicle to be titled (Maryland Department of Transportation Website, 2019). So, if any consumer purchases EVs in March, they could still apply for the tax credit for the 2017 -2018 fiscal year.

In my data set, I have the information about the delivery-date of each of the vehicles from the dealer. So, it seems more logical to me to use 20th March as my cut point rather than July 1 (see Appendix A).

Data

The analysis is based on a daily dealer sales record of vehicles in Maryland State. The sales record is separated by fuel type along with model, price, and vehicle type (truck/van/car, etc.) for the calendar year 2014 to February 2019. This data set contains 2.8 million vehicle transactions. It is a unique dataset, which is collected from the Maryland Department of Transportation Motor Vehicle Administration (MDT MVA).

As I mentioned above, our cut point is 20th March 2017 when the policy is first announced publicly. This indicates, in our dataset, we have 168 weeks of pre-period data and 102 weeks of post-period data. However, I aggregated the daily data into a weekly level. I then took the mean weekly price for necessary vehicle types over this 5-year period.

In this analysis, I omit all the hybrid vehicles. The reason being, in Maryland’s tax program, along with electric cars, some “qualified plug-in hybrid" vehicles are also included. But from the given information of my data, I could not figure out which hybrid cars are conventional hybrid and thus not included in the policy, and which are “qualified plug-in hybrids” that are included. So, I drop all the hybrid models to avoid any potential bias.

Table 1.1 shows the summary statistics of the variables in my model for both the pre-policy and the post-policy period.

Table 1.1

Summary Statistics for Pre & Post-Policy Period

Weekly measure	Mean	Median	Min	Max	Total
Pre period (January 1, 2014- March 20, 2017)					
Electric car sale	9.65	8	1	49	1622 (.097%)
Gasoline car sale	8830.2	8716	4337	13323	1483473 (88.9%)
Diesel car sale	210.04	204.5	107	358	35287 (2.11%)
Flex-fuel car sale	886.02	888.5	425	1270	148852 (8.92%)
Electric car price ($)	28768.64	28676.26	10567.67	64044.38	--
Gasoline car price ($)	24551.84	24491.89	21497.26	27788.34	--
Diesel car price ($)	48606.33	47109.68	37028.17	65637.82	--
Median HH income ($)	78869	77573	76,668	82747	--
Post period (March 21, 2017- February 28, 2019)					
Electric car sale	67.88	49.5	14	335	6924 (.67%)
Gasoline car sale	9062.09	8898	6677	11898	924333 (89.63)
Diesel car sale	194.35	191	132	332	19824 (1.92%)
Flex-fuel car sale	785.13	771	541	1097	80083 (7.77%)
Electric car price ($)	58091.98	57051.58	37127.42	84078.92	--
Gasoline car price ($)	25857.05	25706.72	24170.27	28854.81	--
Diesel car price ($)	52723.4	52629.9	44342.67	62155.52	--
Median HH income ($)	82995	82995	82747	83242	--
Total sale= 2700398		Total sale (pre)=1669234		Total sale (post)= 1031164	

Figure 1.1

Electric Vehicle Sales Before & After the Tax Credit Policy.

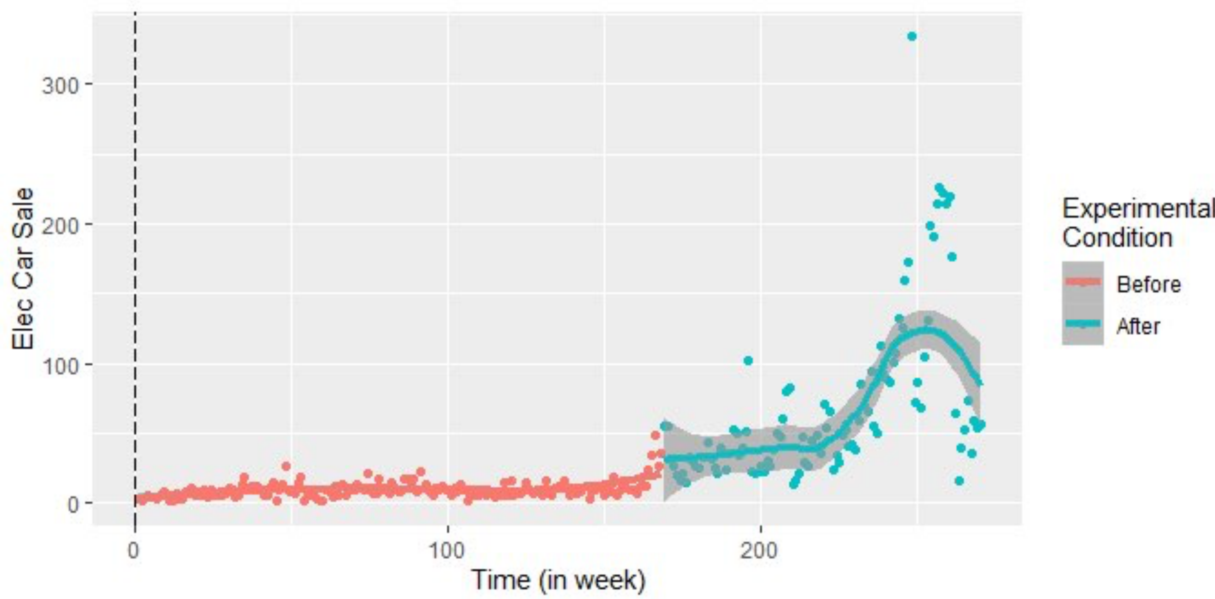


Figure 1.1 shows a graphical depiction of Electric car sales before and after the tax credit program. This plot may give a general idea about the sales pattern of electric vehicles. Here, red and blue lines are smoother for the dotted plots.

Theoretical Background & Model Specifications

Synthetic Control

The traditional synthetic control (SCM) by Abadie and Gardeazabal (2003) and Abadie et al. (2010) is an approach to determine the treatment effect without randomized controls that goes farther along with general pre-post comparisons of means. With this method, a number of untreated time series are optimally weighted according to their fit to the model outcome in the pre-intervention period. After that, they are combined into a composite time series to which the treatment group is compared. This difference is used to estimate the counterfactual scenario, and it allows variation of observed and unobserved predictors over time.

In this study, however, I use the Bayesian structural time series (BSTS) approach to construct the synthetic control that uses Gibbs sampling to estimate the model on the pre-treatment period and then iterates each sampling trajectory forward using the estimated parameters to construct the post-intervention counterfactual. This approach differs from the traditional synthetic control approach that explicitly models the outcome of the treated unit. It also includes information from the post-intervention period for the control units. In this way, the BSTS approach produces a dynamic forecast. Besides, it can more flexibly include time-series effects such as trends and seasonality.

Bayesian Structural Time-Series Models

Structural time-series models are state-space models for time-series data. This model starts by defining two equations:

$$y_t = Z^T_t \alpha_t + \varepsilon_t \tag{1}$$

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \tag{2}$$

Where, $\varepsilon_t \sim N(0, \sigma_t^2)$ and $\eta_t \sim N(0, Q_t)$ are independent of all other unknowns. Equation (1) is the observation equation; it links the observed data y_t to a latent d-dimensional state vector α_t. Equation (2) is the state equation; it governs the evolution of the state vector α_t through time. In the present paper, y_t is a scalar observation, Z_t is a d-dimensional output vector, T_t is a $d \times d$ transition matrix, R_t is a $d \times q$ control matrix, ε_t is a scalar observation error with noise variance σ_t, and η_t is a q-dimensional system error with a $q \times q$ state-diffusion matrix Q_t, where $q \leq d$.

The above specification is advantageous as it allows us to incorporate a linear trend in the state variable (α_t) as well as the seasonality and the additional state variable.

The local trends model from above can be directly interpreted by its components. If we decompose the model as a sum of trend component μ_t and regression component λ_t, we can rewrite it as follows:

$$y_{0t} = \mu_t + \lambda_t + u_t,\ u_t \sim N\,(0,\ \sigma^2{}_u) \tag{3}$$

In the present case, the response variable is EV sales at weekly level, and regression components are a set of untreated control units, such as average EV price, gasoline vehicle sale, diesel vehicle sale, flex-fuel vehicle sale, average diesel vehicle price, average gasoline vehicle price, average flex-fuel vehicle price and median household income of Maryland.

The Bayesian model is asymptotically unbiased because this is the exact data-generating model; the posterior distribution would generally converge to a point mass on its actual value as the number of post-intervention time points goes to infinity (Brodersen, et al. 2015). Some other advantages of this BSTS approach are, we can report statistics such as the average absolute, relative, and cumulative effect caused by the intervention, including their confidence intervals (CIs). The CI can be considered as the region of firmest subjective belief, within which an unobserved parameter falls (Jaynes & Kempthorne, 1976).

Components of State

Local Level Model. The first component of our model is a local level model which is a popular trend model choice defined by the equation

$$\mu_{t+1} = \mu_t + \eta_{\mu,t} \tag{4}$$

Where, $\eta_{\mu,t} \sim N(0,\sigma_\delta^2)$.The μ_t component is the value of the trend at time t.

Seasonality. We have some commonly used state-component models to account for seasonality. The most frequently used model is

$$\gamma_t = -\sum_{s=0}^{S-1}(\gamma_{t-s}) + \eta_t \tag{5}$$

Where S represents the number of seasons, and γ_{t-s} denotes their joint contribution to the observed response y_t. The state in this model consists of the S −1 most recent seasonal effects. The mean value of γ_t is such that the total seasonal effect would be zero when we sum over S seasons. For example, if we set S = 4 to capture four seasons per year, the mean of the spring coefficient will be,

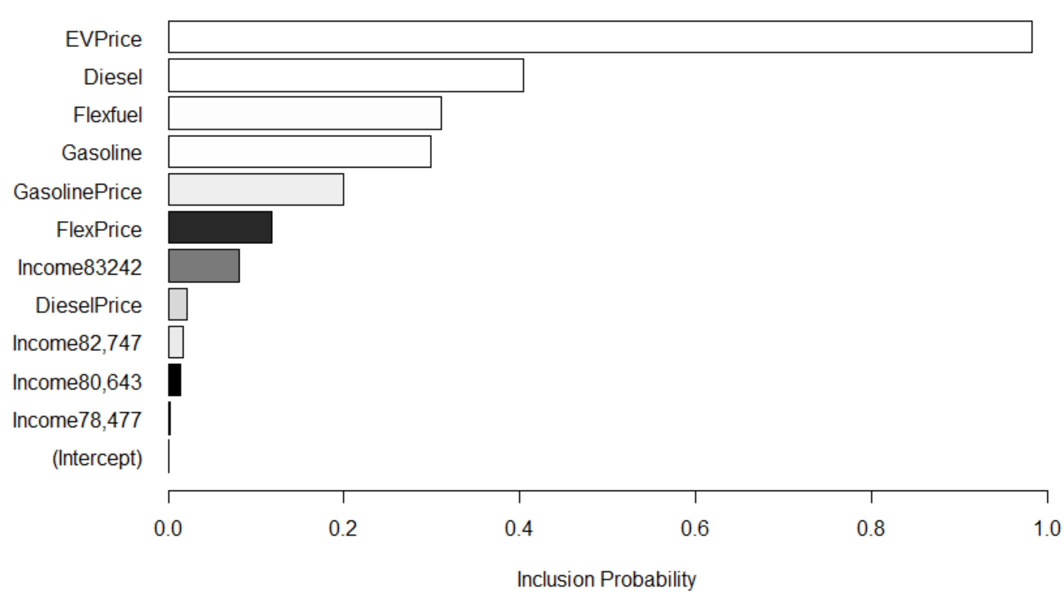
−1 × (winter+ summer+ fall)

The preceding seasonal model can be generalized to allow for multiple seasonal components with different periods. When modeling weakly data, for example, I set S = 52 annual cycles. In the data set, I have a total of 270 weeks starting from January 2014 to February 2019.

Contemporaneous Covariates with Static Coefficients. In this model, covariates are a set of untreated control units, as mentioned before. Control time series that received no treatment is vital to this method for obtaining accurate counterfactual predictions since they account for variance components that are shared by the series. A natural way of including a control series in the model is through linear regression. Here, our coefficients are static.

Figure 1.2

Inclusion Probability of all the Covariates for the BSTS Model



In Figure 1.2, a white bar indicates that the predictor has a positive relationship with consumer sentiment, and a black bar indicates a negative relationship. The size of the bar measures the proportion of the estimated models in which that predictor was present. In the state-space form, we can write a static regression by setting $Z_t = \beta^T x_t$ and $\alpha_t = 1$.

One crucial advantage of working in a fully Bayesian treatment is that we do not need a fixed set of covariates. The "spike-and-slab prior" allows the model to integrate out the posterior uncertainty about which covariates to include and how they would influence model predictions, which avoids overfitting. All covariates are assumed to be contemporaneous.

Prior Distributions and Prior Elicitation

The unknown parameters $\boldsymbol{\theta}$ in this system are the variance terms and the regression coefficients:

$$\boldsymbol{\theta}\colon \{\sigma_u^2, \sigma_\delta^2, \boldsymbol{\beta}\} \tag{6}$$

And let $\alpha = (\alpha_1, \ldots, \alpha_m)$ denote the full state sequence. This study adopts a Bayesian approach to inference by specifying a prior distribution $p(\boldsymbol{\theta})$ on the model parameters as well as a distribution $p(\boldsymbol{\theta}, \boldsymbol{\alpha}|y)$ on the initial state values. We may then sample from $p(\boldsymbol{\theta}, \boldsymbol{\alpha}|y)$ using Markov Chain Monte Carlo (MCMC) through a Gibbs sampler. We can then draw predictions of the counterfactual from $p(\boldsymbol{\theta}, \boldsymbol{\alpha}|y)$. I define an inverse gamma prior to the state error variance parameter and a "spike-and-slab" prior for the regression coefficients.

A spike-and-slab prior combines point mass at zero (the "spike"), for an unknown subset of zero coefficients, with a weakly informative distribution on the complementary set of nonzero coefficients (the "slab"). The spike part is a Bernoulli distribution, and the slab part is a weakly informative normal-inverse-gamma distribution.

Inference

Posterior inference in this model can be broken down into three pieces. First, I simulate draws of the model parameters $\boldsymbol{\theta}$ and the state vector α given the observed data $y_{1:n}$ in the training period. Second, I use the posterior simulations to simulate from the posterior predictive distribution $p(\tilde{y}_{n+1:m}|y_{1:n})$ over the counterfactual time series $\tilde{y}_{n+1:m}$ given the observed pre-intervention activity $y_{1:n}$.

Third, I use the posterior predictive samples to compute the posterior distribution of the pointwise impact $y_t - \tilde{y}_t$ for each $t = 1, \ldots, m$. I use the same samples to obtain the posterior distribution of cumulative impact.

We are primarily interested in the posterior over model parameters and states $p(\boldsymbol{\theta},\alpha|y_{1:n})$, and at the same time, the causal impact analyses are concerned with the posterior incremental effect,

$$p(\tilde{y}_{n+1:m}|y_{1:n}, x_{1:m}) \tag{7}$$

The density in the above equation is defined precisely for that portion of the time series which is unobserved: the counterfactual market response $\tilde{y}_{n+1}, \ldots, \tilde{y}_m$ that would have been observed in the treated market, after the intervention, in the absence of treatment.

The posterior predictive density in this equation is defined as a joint distribution over all counterfactual data points, rather than as an assemble of pointwise univariate distributions. This ensures that we correctly transmit the serial structure determined on pre-intervention data to the trajectory of counterfactuals.

Causal Impact

To find the best fit for my model (see Appendix B), I run several different possible specifications with various state components. The lowest AIC (Akaike Information Criterion) value of these models indicates the best fit (Akaike, 1974). After selecting the best fit BSTS model, I use the estimated states and parameters of the treated unit for the post-intervention time points. Then this procedure is repeated many times. Samples from the posterior predictive distribution over counterfactual activity can be used to obtain samples from the posterior causal effect, that is, the sales of EV. For each draw τ and for each time point

$t = n+1, \ldots, m,$ *we set,*

$$\varphi_t^{(\tau)} = y_t - \tilde{y}_t^{(\tau)} \tag{8}$$

yielding samples from the approximate posterior predictive density of the effect attributed to the intervention.

In addition to its pointwise impact, we can see the cumulative effect of an intervention over time-

$$\sum_{t'=n+1}^{t} \varphi_t^{(\tau)} \tag{9}$$

$\forall t = n+1, \ldots, m.$

I implement BSTS in the R (R Core Team, 2017) programming language with the CausalImpact (Brodersen et al., 2015) package. Unlike more common "micro-econometric" techniques like difference-in-differences, synthetic control, or regression discontinuity, CausalImpact is designed to work with a univariate time series.

However, it is worth mentioning that our time series is long enough to plausibly estimate the parameters we are interested in.

Results

Table 1.2 presents the results of the BSTS analysis, and Figure 3 shows the observed and predicted time-series data.

The result shows that, during the post-intervention period, EV sales had an average value of approximately 68. By contrast, in the absence of an intervention, we would have expected an average response of 33. The 95% interval of this counterfactual prediction is [+19, +48]. To find the absolute effect, we may subtract this prediction from the observed response, which yields an estimate of the causal effect the intervention had on the response variable. This effect is 35 with a 95% confidence interval of [+19, +49].

Table 1.2

The Causal Effect of the Tax Credit on Electric Vehicle Sales

		Actual Effect	Predicted	Predicted Lower-Upper	SD
Actual	Average	68	33	[19- 48]	7.5
	Cumulative	6924	3338	[1898- 4944]	760.8
		Absolute Effect	Absolute Lower	Absolute Upper	SD
Absolute	Average	35	19	49	7.5
	Cumulative	3586	1980	5026	760.8
		Relative Effect	Relative Lower	Relative Upper	SD
Relative		107%	59%	151%	23%
Posterior tail area probability, P=0.0034					
Posterior probability of a causal effect= 99.96577%					

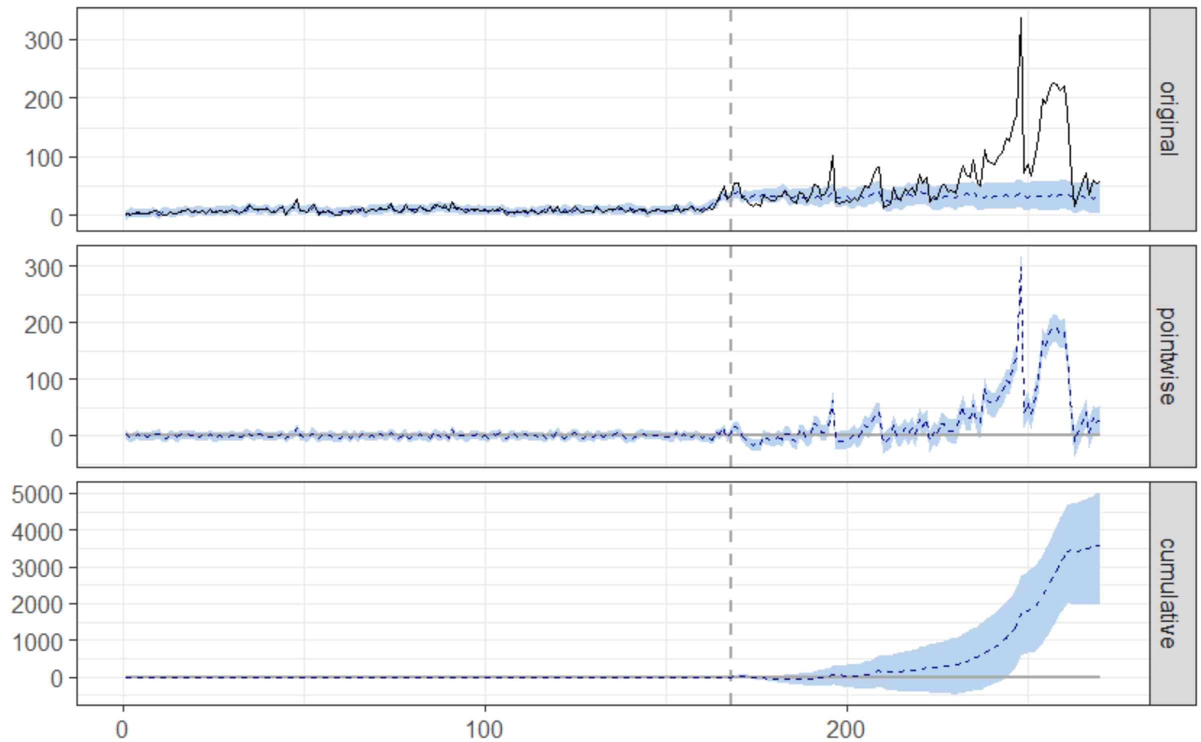
Results also show a cumulative effect by summing up the individual data points during the post-intervention period. The EV sales had an overall value of 6.92K. By contrast, had the intervention not taken place, we would have expected a sum of 3.34K. The 95% interval of this prediction is [+1.90K, +4.94K]. In relative terms, the response variable showed an increase of 107%. The 95% interval of this percentage is [+59%, +151%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations

The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0). This means the causal effect is statistically highly significant.

Also, our confidence interval band is in the lower range, which indicates that our estimate is strong, and there is less uncertainty.

Figure 1.3

Electric Vehicle Sales Before and After the Tax Credit Program



In this figure, the upper plots ("original") show the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% credible interval, according to the Bayesian structural time series model. The middle plots ("pointwise") show the average difference between the observed and estimated values. Another way of visualizing posterior inferences is by employing a cumulative impact plot, which is our lower plot. It shows, for each day, the summed effect up to that day.

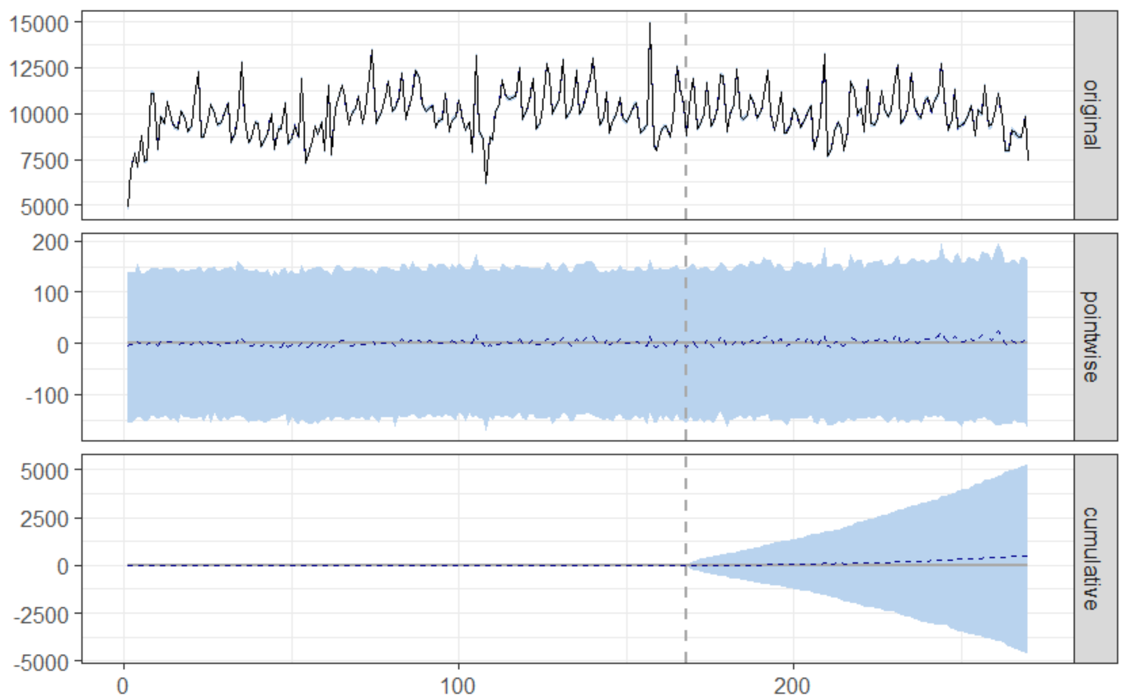
Robustness Check

Causal Impact on Other Fuel Type Vehicles

BSTS analysis for other fuel type vehicles sales reveals that there is no policy effect on these vehicles sales in the post intervention period.

Figure 1.4

Sales For Other Types of Vehicles Combined Before and After Tax Credit Program



In Figure 1.4, there is no increase in sales after the policy is implemented. The plot shows the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% credible interval (blue area), according to the Bayesian structural time series model.

Table 1.3 shows the results of the BSTS analysis for different fuel type vehicles other than EV. The first column of this table shows the result of the policy effect on gasoline, diesel, and flex-fuel vehicles combined. The next three columns present the result of Bayesian analysis for these three types of vehicles separately.

Table 1.3

Average Effect of Tax Credit Program on Other Fuel-Type Vehicles

	Other Fuel Combined	Diesel	Gasoline	Flex-fuel
Actual effect	10,040	194	9062	785
Predicted	10,040	204	8185	896
95% CI	[9,990,10,090]	[144,266]	[6751,9741]	[734,1069]
Absolute effect	4.5	-9.9	877	-111
95% CI	[-45,52]	[-71,50]	[-679,2311]	[-284,51]
Relative effect	0.045%	-4.8%	11%	-12%
95% CI	[-0.45%,0.52%]	[-35%,25%]	[-8.3%,28%]	[-32%,5.7%]
Posterior tail area P	0.41441	0.36657	0.12553	0.07734
Prob. of a causal effect	59%	63%	87%	92%

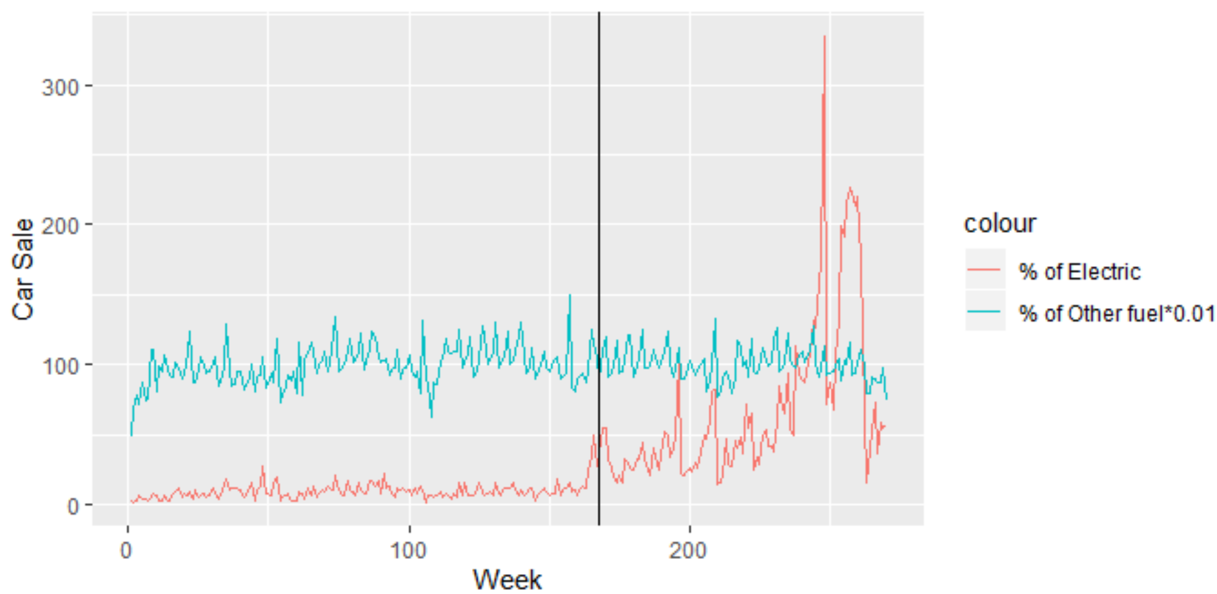
I run the same analysis for diesel, gasoline, and flex-fuel vehicles separately and found no policy effect either. I remove those tables and graphs for the sake of brevity.

Sales Pattern

Figure 1.5 depicts the sales pattern of EVs in comparison with other fuel type vehicles like gasoline, diesel, and flex-fuel. Although EV market share is still small, after the intervention, EV shows an apparent increase in sales. Figure 5 shows the relationship of EV with other fuel type vehicle sales over time.

Figure 1.5

Sales Patterns of EV and Other Fuel Types of Vehicles

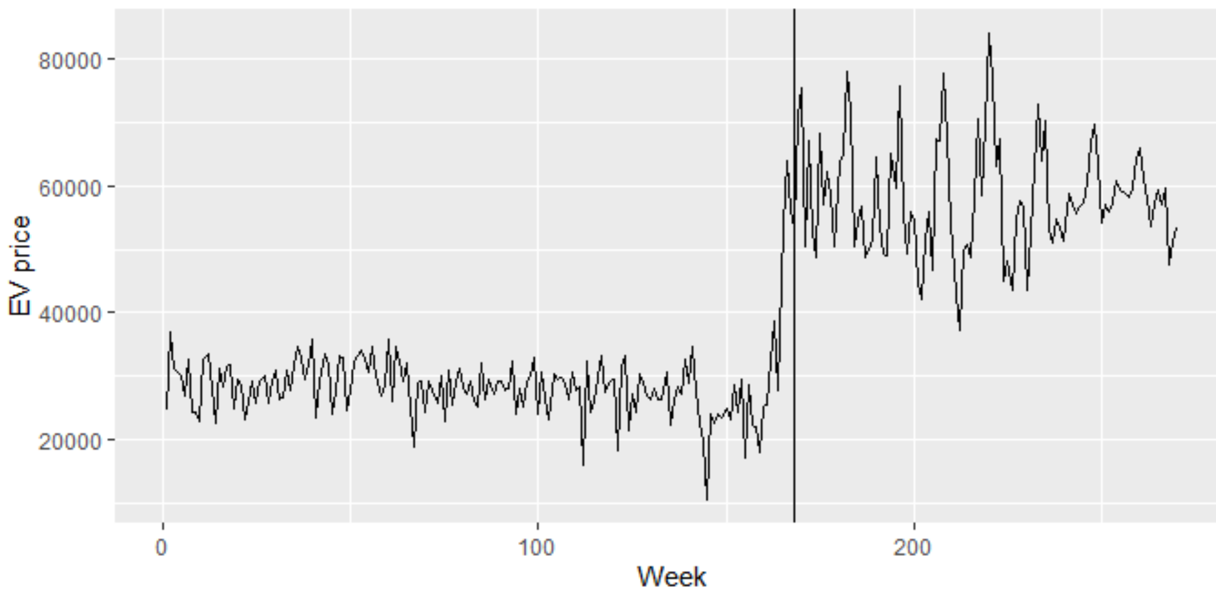


EV Price Change

To see if there is any drop in the price level near our cut-off point, I plot the average weekly EV price. If there is any price drop, our result of the tax credit effect may not be valid, but Figure 1.6 instead shows a price jump just before the cut point. It seems like people started to buy expensive EVs when the tax credit was announced, or we may say people stopped buying cheaper EVs after the tax credit was announced. Moreover, the tax credit only allocates $3000 for each EV, but the price range increased so much higher than that. Also, the tax credit does not apply to a vehicle with a price that exceeds $63000. However, we can see that those expensive vehicle purchases increased after the implementation of the tax credit.

Figure 1.6

Average EV Price Over Time



In this figure, the black vertical line represents the cut point. Nevertheless, all the above results/plots suggest that the tax credit policy itself had a positive effect on the EV market.

Discussion & Conclusion

This study has several limitations. As I mentioned before, I omit all the hybrid vehicles because I cannot differentiate between a conventional hybrid and a plug-in hybrid from the dataset I used.

In addition, there are some other incentives in Maryland State for EV, for example, qualified vehicles can use the HOV lane, and there are more charging stations available now for people's convenience. I could not measure these incentives in this model. However, Maryland is one of the wealthiest states in the USA. According to the ACS 2019 survey of median household income, Maryland is actually the number one richest state now. Moreover, electric vehicles are still considered an expensive consumer choice. So, there is a chance that this type of policy effect may not be as effective in other states also.

Nevertheless, all the above analysis finds that the tax credit policy had a definite positive effect on the Maryland EV market. The actual average EV sales more than doubled than our counterfactual prediction. Our estimate is highly significant; moreover, our confidence interval band is smaller, which indicates less uncertainty.

However, Maryland State announced ambitious goals when implementing this policy, which is to achieve 300,000 EVs and PHEVs on the road by 2025. According to our result, we see during our over 23 months of post-intervention period, around seven thousand EVs were adopted. So, assuming this rate will continue, we can roughly calculate that only around Thirty thousand EVs will be adopted by 2025. Although we excluded Plug-in Hybrid (PHEV) from our estimate, this amount seems very lower than the stated goal, which is 300,000.

Moreover, according to Maryland State's website, this state already burned through the funds of 6 million dollars. So, the availability of tax credit for the 2019-2020 fiscal year becomes uncertain. Unless the state can come up with more funding, it is likely to see a decrease in sales of EV and PHEV.

In the future, I want to think about capturing the trade-offs and substitution patterns that the tax incentive created. For example, whether someone that would not have been willing/ able is now willing/ able to buy a vehicle or whether they are switching the purchase choice. If so, from what vehicle are they switching? Are consumers switching from hybrid vehicles or gasoline vehicles? If they are only switching from Hybrid vehicles, then the effect would not be so high in terms of environmental perspective because hybrid vehicles are more energy-efficient than diesel/gasoline cars.

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Appendices

APPENDIX A: DIFFERENT CUT-POINT

As I mentioned before, I chose my cut point to be 20th March 2017. But the policy was effective formally from 1st July 2017. To check if there is an anomaly, I run my model with cut point 1st July as well.

Figure A1

Causal Impact of the tax credit with cut point 1st July 2017

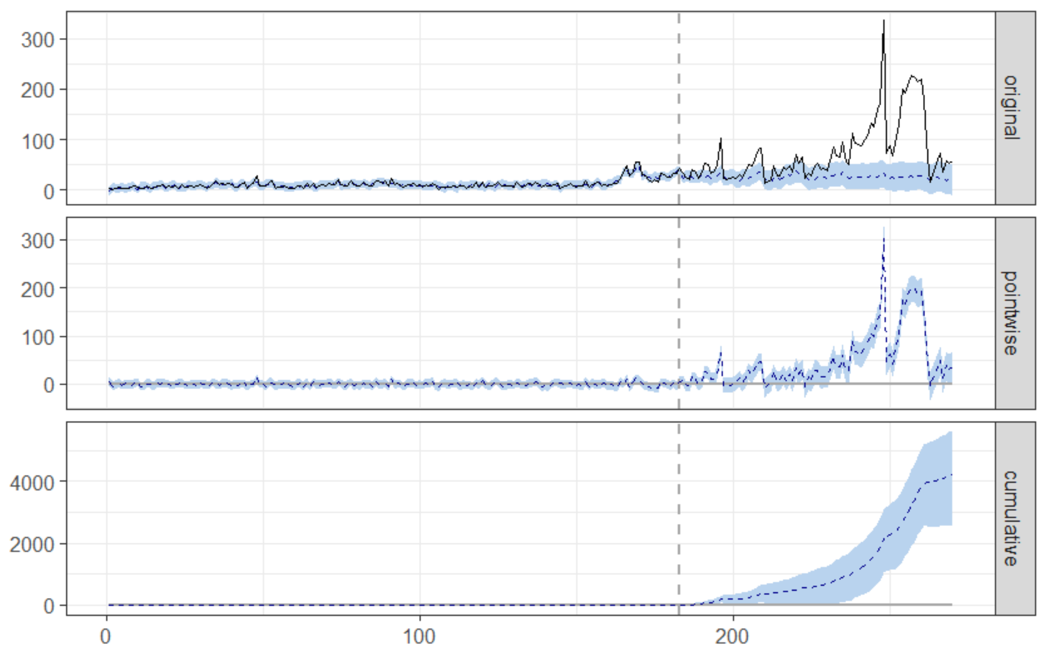


Figure A1 shows the Causal Impact of the tax credit with cut point 1st July 2017. We can see some prior jump in the figure of sales before the new cut point, which can be explained by the reason I mentioned earlier that it takes some time for customers and dealers to titling the vehicle officially so that they were eligible for the tax credit. In this case, the actual effect is higher, where the cumulative effect is lower. The confidence interval span increased, which indicates a little more uncertainty. These suggest that the 20th March cut point is the better representation of this policy.

Table A1

Causal Impact with a Different Cut Point

		Actual Effect	Predicted	Predicted Lower-Upper	SD
Actual	Average	74	28	[9.6- 49]	9.8
	Cumulative	6460	2447	[838.5- 4291]	856.6
		Absolute Effect	Absolute Lower	Absolute Upper	SD
Absolute	Average	46	25	65	9.8
	Cumulative	6460	2169	5622	856.6
		Relative Effect	Relative Lower	Relative Upper	SD
Relative		164%	89%	230%	35%

Posterior tail area probability, P= P=0.0012

Posterior probability of a causal effect= 99.898%

APPENDIX B: MODEL CHOICE

To find the best fit for my model, I run several different possible specifications with various state components. I then count the AIC (Akaike Information Criterion) of each of these seven models.

$$AIC= 2k-2\ln(L)$$

Where k is the number of parameters, and ln(L) is the natural log-likelihood function.

The lowest AIC tells us which model is our best fit. I found model 1, which is a local-level trend with regressor or seasonality, is the best model as this model has the lowest AIC value [25].

Table B1

AIC Values for Seven Different Combinations of Models

Model	Model configuration	AIC Value
Model 1 (Lowest)	Local-level model with regressor but no seasonality	1022.21
Model 2	Local linear model with regressor but no seasonality	1036.65
Model 3	Local-level model without seasonality or regressor	1029.17
Model 4	Local linear model without seasonality or regressor	1041.404
Model 5	Local linear model with seasonality but no regressor	1374.92
Model 6	Local-level model, with regressor and seasonality	1362.97
Model 7	Local linear model, with regressor and seasonality	1375.24

AIC value suggests that the best configuration of our model is a local-level trend with regressor but no seasonality, which is model 1 in our table.

CHAPTER II

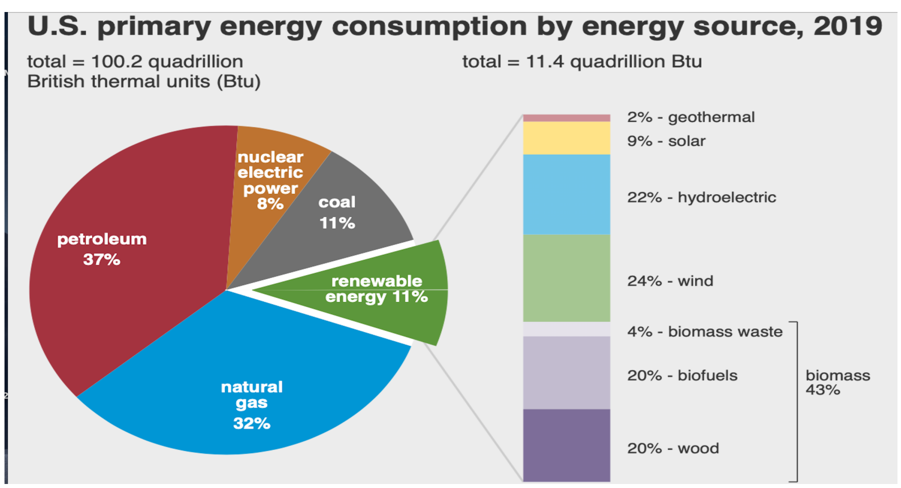
IMPACT OF ELECTRIC VEHICLE ADOPTION ON ELECTRICITY CONSUMPTION AND GENERATION: EVIDENCE FROM CALIFORNIA

The United States is the third-largest electric vehicle (EV) market, following China and Europe. The State of California alone accounted for half of all new 2019 electric vehicle sales in the USA. Federal and state-level actions, including regulations, financial and non-financial incentives for consumers, charging infrastructure development, and consumer awareness programs, are playing an essential role in increasing EV adoption. These incentives are important because upfront purchase cost is a barrier (Bui et al., 2020). Apart from federal incentives, 40 states currently have their own EV incentive, rebate, or emission control programs (Alternative Fuel Data Center, 2020). The government is trying to promote electric vehicles, mostly due to environmental concerns. The U.S. Department of Energy (DOE) report states that increasing passenger vehicle efficiency and reducing the use of petroleum-based fuels can reduce consumers' fuel costs, support the domestic industry, minimize pollution, and increase energy security (DOE, 2014, p.7). The DOE supports EV as a solution for the challenge of providing affordable, clean, secure transportation. The government also supports plug-in-hybrid vehicles (PEVs) that are powered at least in part by electricity. On September 8, 2011, Energy Secretary Steven Chu announced the Clean Cities Community Readiness and Planning for Plug-In Electric Vehicles and Charging Infrastructure awards. These awards helped communities forge public-private partnerships to take strategies to support the adoption of PEVs and charging infrastructure installation. These 16 awards, totaling $8.5 million, helped prepare 24 U.S. states and the District of Columbia to adopt PEV technologies to reduce U.S. petroleum dependence and build the foundation for a clean transportation system (DOE, 2014).

While the changes towards electric energy sources represent a positive change, that progress is diminished by the fact that coal, natural gas, and nuclear fuels are still the most-used electricity generation sources nationwide. Natural gas and, to a certain extent, and shale oil remains relatively cheap and reliable energy sources. Despite the prevalence of non-renewable fuels, electric power can also be derived from renewable sources, including wind power, hydropower, and solar power (U.S. Energy Information Administration [EIA], 2020). Below two figures show the energy generation share and trend by sources.

Figure 2.1

U.S Primary Consumption of Electricity Share[1] by Sources in 2019



[1] Sum of the components may not equal to 100% due to independent rounding
1 Btu= 0.293071 Watt-hour
Source: U.S Energy Information Administration, *Monthly Energy Review,* Table 1.3 and 10.1, April 2020, Preliminary data

Figure 2.2

U.S Primary Energy Consumption by Major Sources from 1950 to 2019

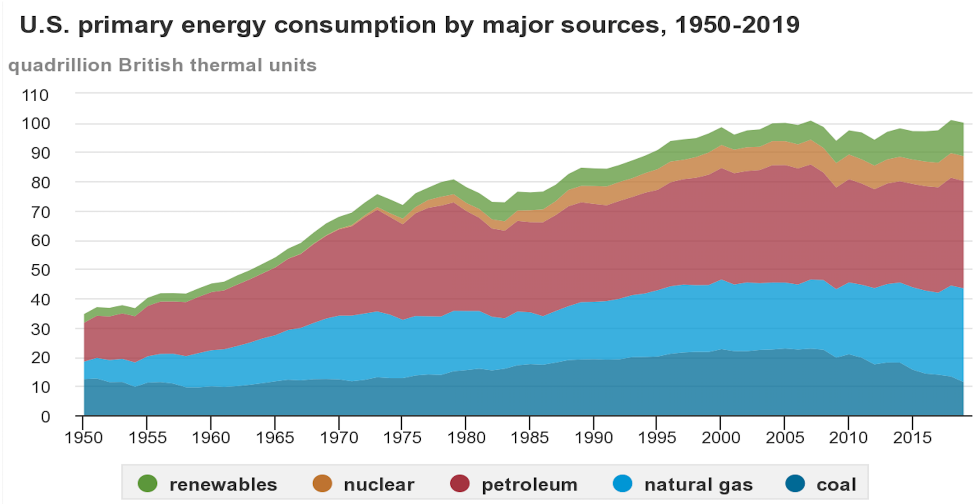


Figure 2.1 and Figure 2.2 show that electricity generation still relies mainly on fossil fuel, primarily responsible for emitting the major air pollutants in the USA. US Department of Energy report contends, "Power plants are the largest source of sulfur dioxide (SO2) emissions in the United States... Power generation from fossil fuels, biomass, and waste contributes to air pollutants that adversely impact human health and the environment" (Oak Ridge National Laboratory, 2017, p vii). This has policy implications regarding EV adoption, which may increase electricity consumption.

This study aims to examine the impact of EV adoption on electricity consumption and, eventually, on electricity generation from renewable sources. As stated by the DOE website, an average EV's electricity consumption is 0.34 kWh/km, and an average American drives 46 km daily. So, per capita, monthly electricity consumption due to EV is roughly 470 kWh for an EV driver. In the USA, the average residential electricity consumption per person is 909 kWh each month (DOE, 2020); this data suggests a person's electricity consumption due to EV could be on the order of 50% of one's residential electricity consumption. The DOE website also states that, based on the national average of 12.6 cents/kWh, fully charging an all-electric vehicle with a 100-mile range and depleted battery would cost about the same as operating an average central air conditioner for six hours. These estimates indicate that EVs can cause an increase in electricity demand, and so that electricity generation sources should also be analyzed.

This study consists of two major parts. First, using county-level monthly data from California for the year from 2010 to 2019, I estimate the effect of EV adoption on residential and commercial electricity consumption. By employing fixed-effect panel regression, this study finds that each electric vehicle charging station significantly increases the residential and commercial electricity consumption per county by 0.12%. Second, after establishing the relationship between EV adoption and electricity consumption, this study explores the electricity generation pattern by sources, especially whether there is any significant relationship between excess electricity consumption and renewable electricity generation. By analyzing ten years of electricity generation information in California, this study finds an increased electricity consumption significantly reduces renewable energy share.

The rest of this study is organized as follows: first, I give a brief literature review in section 2. Section 3 presents an overview of the data, and section 4 discusses the model specification. I offer the result of our analysis in section 5 before concluding in Section 6, along with discussions of the limitations of this study.

Literature Review

Analysis of electricity consumption due to electric vehicles' adoption is absent in the economics literature so far. Most studies about EV adoption focused on purchasing patterns due to incentives using various consumer choice models. However, studies about electricity consumption due to the adoption of new technologies are available. Su (2019), in his research about residential electricity demand in Taiwan, found that the effects of urbanization and energy poverty have a significant positive impact on energy consumption. He used Air cooler (AC) as an exogenous variable to account for the differences between urban and rural areas. Hung and Huang (2015) also estimated the same relationship using dynamic panel data.

Holtsmark et al. (2014) studied Norwegian subsidy policies for EV purchasers and concluded that the sales of EVs in Norway increased rapidly as a result of these policies. Due to the subsidies, driving an EV implies very low costs to the owner on the margin, probably leading to more driving at the expense of public transport and cycling. Moreover, because most EVs' driving range is low, the policy gives Norwegian households incentives to purchase a second car, again stimulating the use of private vehicles instead of public transport and cycling. This study also analyzed the emission level due to the production of two models of EVs and their batteries. All of these lead to more pollution. The authors concluded that the EV policy could not be justified.

There are several environmental engineering fields of studies that address this question with different aspects. For instance, Foley et al. (2012) examined the Irish government's target in 2008 that 10% of all vehicles in the transport fleet be powered by electricity by 2020. The study confirms that off-peak charging is more beneficial than peak charging and that charging EVs will contribute 1.45% energy supply to the 10% renewable energy in transport target, which also contributes to a certain amount of CO_2.

Muratori (2018) found that even if the total PEV market share remains limited, high PEV adoption clusters can be found in certain areas. The results show that the introduction of one single PEV in a residential distribution network consisting of six households can potentially increase the distribution transformers' peak load factor if Level 2 (a type of EV charger) charging is considered, which can lead to a significant decrease in the expected transformer life. In general, the higher charging level significantly exacerbates the impact of PEV charging on the residential distribution infrastructure.

However, Rolim et al. (2012) collected information about driving behavior by interviewing eleven EV drivers in Lisbon, Portugal, with onboard diaries, including km traveled, kWh charged, and the number of trips per day for five months duration. Results indicate that the EV's adoption impacted everyday routines on 36% of the participants, and 73% observed changes in their driving style. Compared to conventional internal combustion engine vehicles running on gasoline or diesel, EV reveals considerable reductions in energy consumption and CO2 emissions.

Nicholas et al. (2015) estimate to what extent PEVs are more environmentally friendly, than conventional passenger cars in Texas, controlling for the emissions and energy impacts of battery provision and other manufacturing processes. Results indicate that PEVs on today's grid can reduce some types of pollutants in urban areas but generate significantly higher emissions of SO_2 than existing light-duty vehicles. A primary concern for PEV growth is the use of coal for electricity production, but there is a benefit of electrified vehicle miles' energy security.

Data

This study examines empirical data to estimate the effect of EV adoption on electricity consumption and the relationship between electricity generation by renewable sources. Primarily, I use California's county-level monthly data for the year 2010-2019 to find the effect on electricity consumption. California's EV rebate program also started at the beginning of 2010. California has 58 counties, so, there are 6960 monthly observations in the dataset. I have collected electricity consumption and revenue data for different sectors from the California Energy Commission. I then use this information to calculate electricity prices also.

I have to use a proxy variable for the EV adoption data because original EV registration data is not publicly accessible. California state has a rebate program for EV purchasers, which started in 2010. The California Air Resources Board's Clean Vehicle Rebate Project (CVRP) provides rebate checks to California individuals, businesses, and government agencies to purchase or lease eligible clean vehicles, including plug-in hybrid, all-battery, and fuel-cell electric vehicles. According to the CVRP website, rebated vehicles constitute a majority (74%) of new clean-vehicle sales in the state (Center for Sustainable Energy, 2015). We assume that there are no differences in rebate rates across counties. I discuss more detail about this CVRP program and other incentives for electric vehicle supply equipment (EVSE), such as charging stations, in Appendix A.

EV charging Station information is provided by the U.S. Department of Energy and National Renewable Energy Laboratory. In the data set, there is information about the opening date of each station or charging ports. I aggregate the numbers of active stations at the monthly level of each county. In this study, I use connectors and stations interchangeably. In one station, there might be more than one connector to charge more vehicles at a time. I use the number of total connectors. Currently, there are three types of charging stations available. Level 1, level 2, and DC fast. These three settings require different volts and amps and take a different range of times to charge EV. In my model, however, I do not differentiate these types of stations since this study focuses on electricity consumption, not the intensity of the electricity flow at particular times.

Information on different housing units like single-unit, multi-unit, and the mobile unit, are collected from the California state association of counties. I collect per capita personal income, population, and employment data from the Bureau of Economic Analysis (BEA), and U.S. Department of Commerce website. I collect average monthly temperature per county information from the National Centers for Environmental Information of National Oceanic and Atmospheric Administration (NOAA).

Figure 2.3 to Figure 2.7 show the population density by county, the average total electricity consumption of ten years, average per capita electricity consumption, total electric vehicle, and charging station adoption level at the end of 2019. Figure 2.8 shows the percentage of electricity that comes from renewable resources in each county.

Figure 2.3

The Average Population by County in California

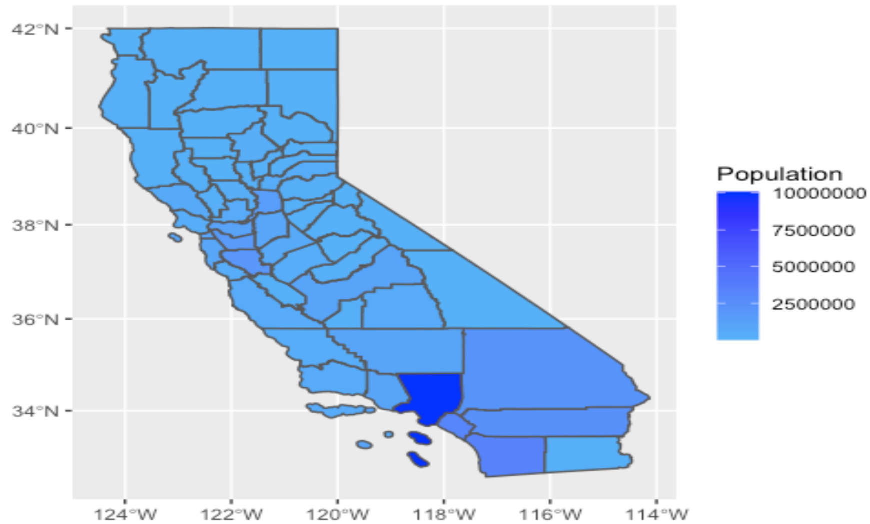


Figure 2.4

Average Electricity Consumption by Counties

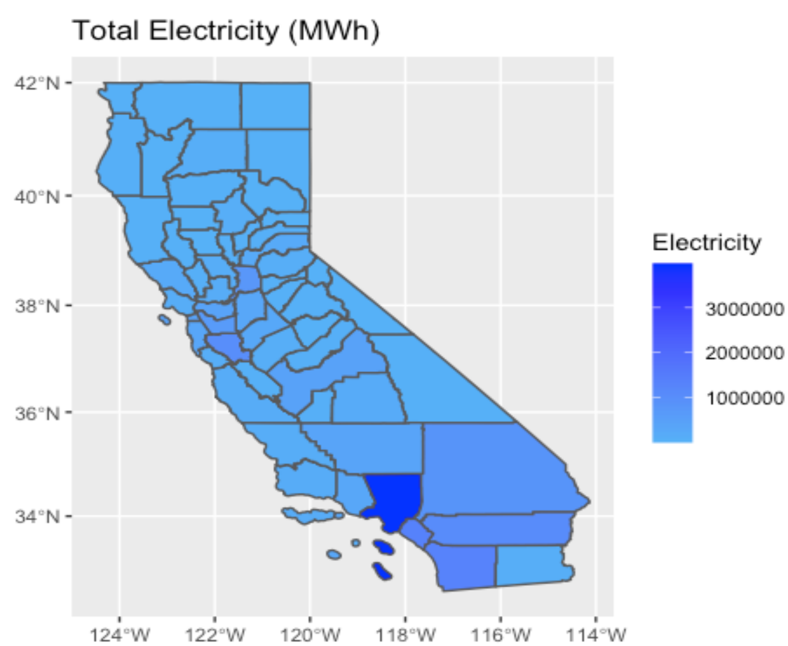


Figure 2.5

Total EV Adoption at the End Of 2019 by Counties

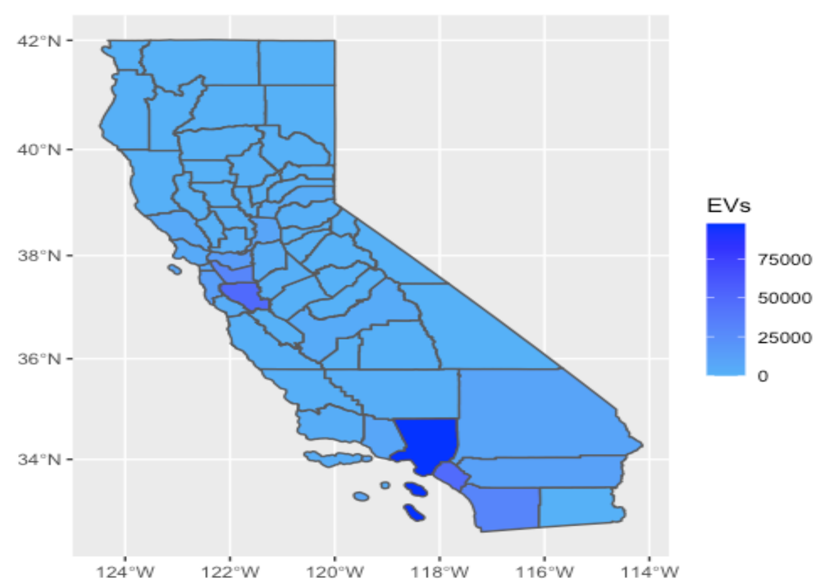


Figure 2.6

Per Capita Average Electricity Consumption by Counties

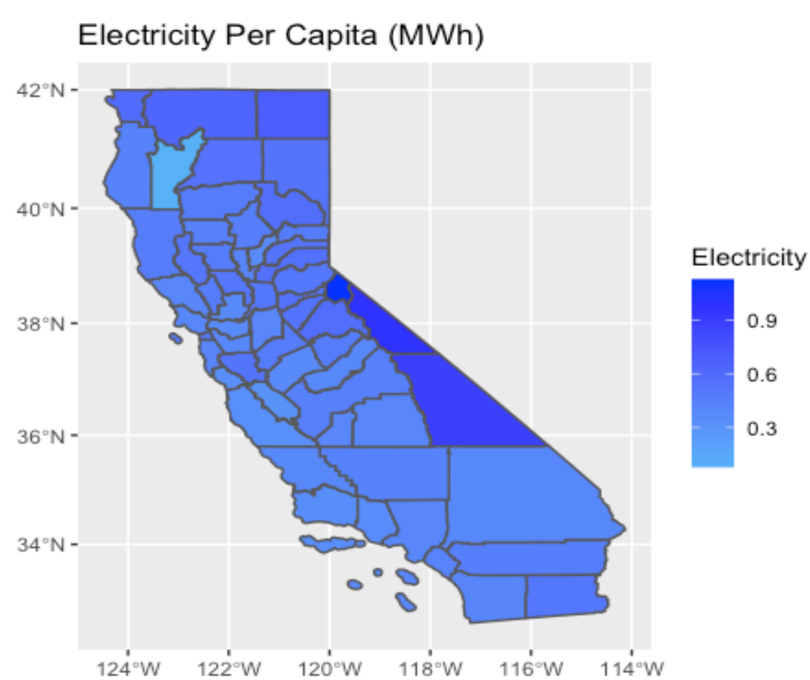


Figure 2.7

Total Charging Station at the End of December 2019 by Counties

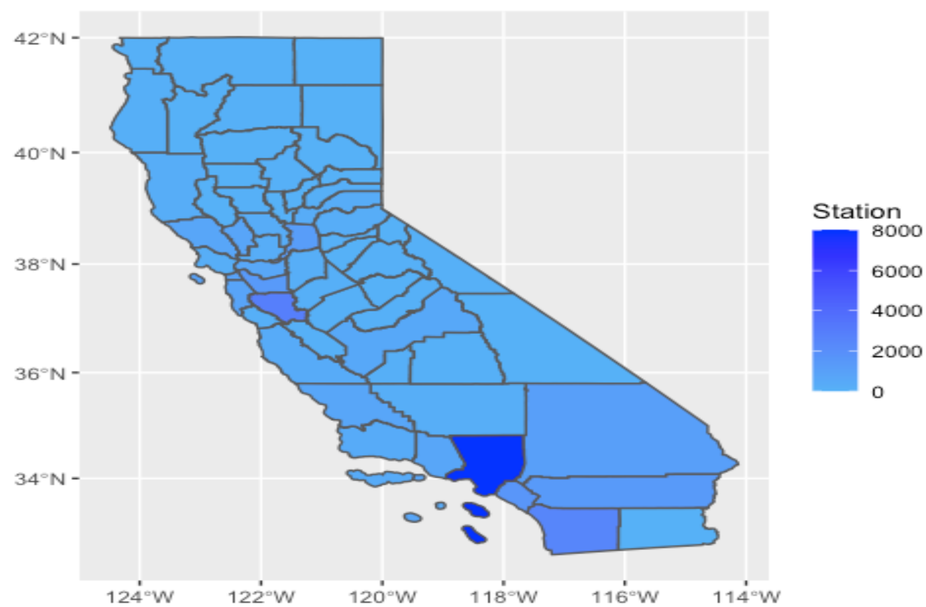
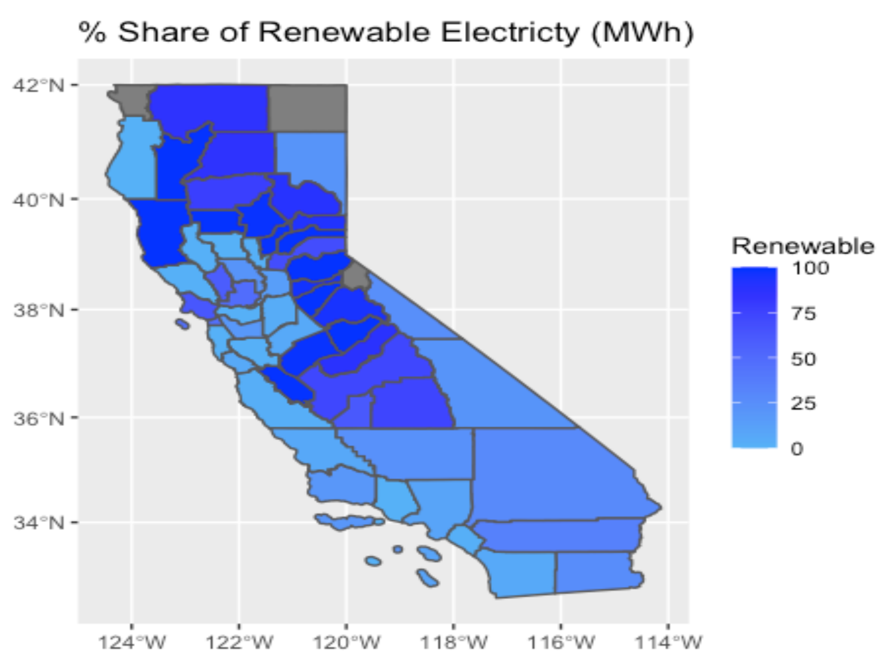


Figure 2.8

Percentage of Electricity Comes from Renewable Sources



Although I did not control for anything to depict the intensity of EV adoption, station constructure, and electricity consumption, these maps might give a general idea about the relationship considered here. Table 2.1 shows the summary statistics of the variables I use in this study. Table 2.2 represents the average per capita electricity consumption for ten most EV adopting counties and ten least EV adopting counties annually for the study period.

Table 2.1
Summary Table

Variables	Mean	St Dev	Min	Max
EV	2052.90	7428.94	0	97538
Station	147.7	494.12	0	8016
Income ($)	49061	18090.95	26717	141735
Population	665831	1441469	1047	10105708
Employment	382226	879935.8	970	6685737
Residential Electricity (MWh)	130518.40	257371.51	328.60	2555402.70
Commercial Electricity (MWh)	149504	336388.80	93	2746909
Residential Electricity Price ($)	159.83	38.77	0.0105	1200.34
Weighted Average Price ($)	151.70	34.36	35.5	635.3
Single housing	155818	292312.52	1049	1965018
Multi housing	74368	205912.60	106	1545580
Mobile housing	9654	14608.09	32	80315
% of Electricity share from Renewable source (MWh)	46.93	40.08	0.000	293.58
Number of observation (N)= 6960				

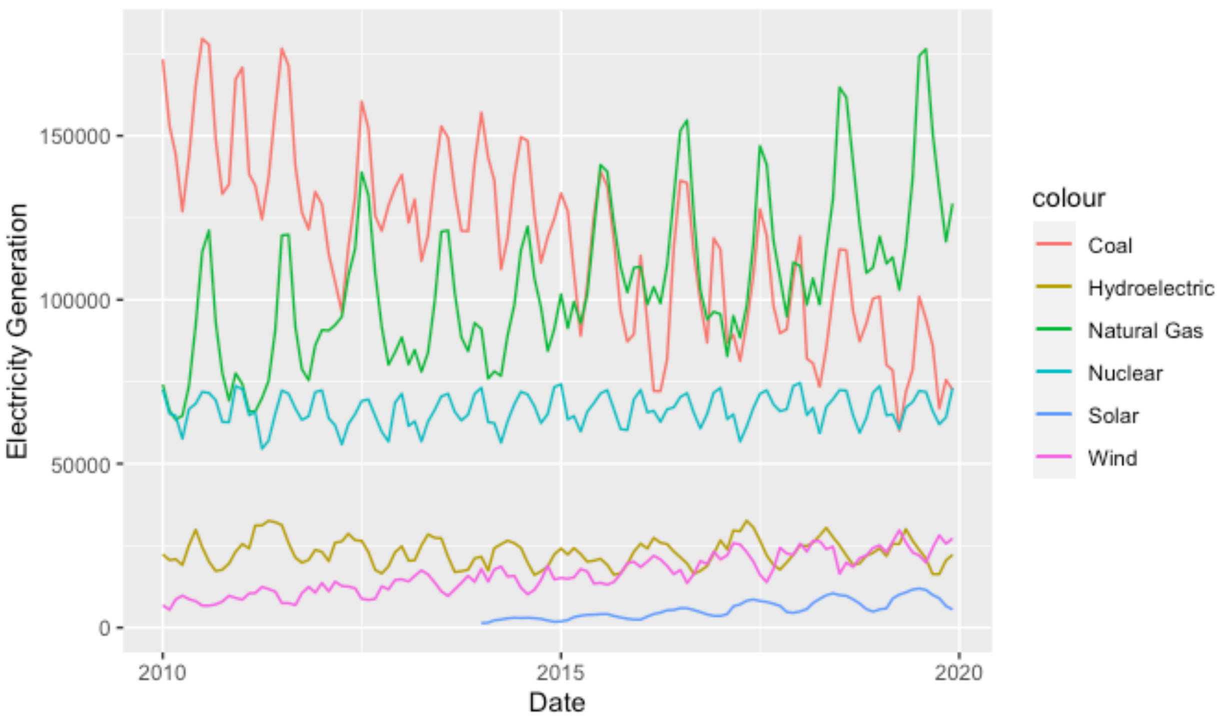
Table 2.2
Per Capita Average Electricity Consumption (MWh) of Ten Highest & Ten Lowest EV Adopting Counties.

	Per capita Electricity Consumption	
Year	Highest ten EV Adopting Counties	Lowest ten EV Adopting Counties
2010	5.196	7.729
2011	5.203	7.449
2012	5.237	7.351
2013	5.169	7.819
2014	5.181	7.276
2015	5.114	7.279
2016	5.061	7.558
2017	5.133	7.713
2018	4.988	7.450
2019	4.954	7.673
Welch Two Sample t-test: t = -34.764, p-value = 3.568e-14		

Moreover, I have collected electricity generation data of California at the yearly level by counties for 2010 to 2019 from the California Energy Commission to estimate the effect of EV adoption on the types of electricity generation by renewable sources. In California, primary electricity sources are coal and natural gas. Major renewable electricity sources are Hydroelectric, solar, and wind. Figure 2.9 shows the electricity generation trend by sources in California State as a whole for the past ten years, and Table 3 shows the summary statistics of the electricity sources.

Figure 2.9

Electricity Generation of California by Sources



(Source: EIA, 2020)

From Figure 2.9, we can see that solar production did not start in California until December 2013. Renewable electricity share in the total electricity production is relatively low in these ten years in California.

Table 2.3

Summary Statistics of Electricity Generation by Sources

	Non-Renewable				Renewable		
	All Fuel	Coal	Natural Gas	Nuclear	Hydroelectric	Solar	Wind
Minimum	287,800	60,008	63,431	54,547	16,074	1,375	5,432
Average	340,978	118,088	104,483	66,475	23,060	5,566	16,249
Maximum	418,693	179,600	176,458	74,649	32,607	11,941	29,711

Number of observation (N) = 580

According to the Table 2.3, in December 2019, total electricity generation in California was 337253.09 thousand MWh. Hydroelectric, solar, and wind combined generated 54929.56 thousand MWh electricity, only 16% of the total electricity generation. The other three sources, coal, natural gas, and nuclear, contribute the most to California's electricity production. Table 2.4 shows the average percentage share of electricity from renewable resources in the ten most EV adopting and ten least EV adopting counties.

Table 2.4

EV Adoption & Renewable Electricity Generation for Ten Highest & Lowest EV Adopting Counties

Highest EV adopting counties				Lowest EV adopting counties			
County	% of renewable electricity	EVs	Station	County	% of renewable electricity	EVs	Station
Los Angeles	9.686	379,538	27,958	Modoc	NA	0	20
Santa Clara	0.8831	208,307	8,430.2	Sierra	92.75	18.7	11
Orange	1.6723	176,010	5,160.6	Alpine	NA	13.60	61.7
San Diego	6.1137	116,925	10,552	Lassen	20.979	23.1	24.8
Alameda	17.7320	118,198	4,713	Trinity	100	46.50	25.0
Contra Costa	0.64937	55,773	1,123.8	Colusa	0	46.0	23
San Mateo	0	54,804	1,797.6	Glenn	100	59.70	0
Riverside	34.184	36,840	5,231	Mono	24.40	51.50	380.6
San Bernardino	27.99	29,062	3,606	Plumas	89.50	57.30	28.9
Sacramento	13.575	27,828	6,185	Inyo	20.706	78.60	43.2

Methodology

EV Adoption on Electricity Consumption

This study constructs a two-way fixed-effect linear regression model where the dependent variable is the monthly electricity consumption over time. I look at residential and commercial electricity because, according to the California Energy Commission, electricity consumption due to EV charging is mostly under residential and commercial sectors. People charge their EVs either at home or at the charging stations. Apart from public charging stations, there is a number of private charging stations in California, and many EV owners adopt relatively simple Level 1 EVSE or the slightly more complex Level 2 EVSE at their residents. People in nearby residents also share the charging facilities with neighbors using mobile apps. For example, California-based startup EVMatch and ampUp are these types of initiatives, which by using people can share their residential charging connectors with others and earn money (CVRP, 2020). So, in my model, I exclude other sectors like the agricultural sector, industrial sector, etc., from this analysis. The electricity consumption for county i at time t is specified as-

$$\begin{gathered} Log(ELECTRIC_{it}) = b_0 + b_1\, Log(EV_{it}) + b_2\, Log(STATION_{it}) + b_3\, Log(POP_{it}) + \\ b_4\, SINGLE_{it} + b_5\, Log(EMPLOY_{it}) + b_6\, Log(INCOME_{it}) + \\ b_7\, Log(HOTMONTH_{it}) + b_8 Log(COLDMONTH_{it}) \\ + b_9\, Log(PRICE_{it}) + \delta_t + \phi_i + u_{it} \end{gathered} \tag{1}$$

Here, *ELECTRIC* is the monthly residential and commercial electricity consumption for each county. *EV* is the number of electric vehicle rebate application numbers in a specific county and month, and this is our primary variable of interest. In the dataset, there is information about the application date. I take the cumulative sum of the numbers of applications for each county at the monthly level. In my model, I am assuming people file their applications in the same month they purchase EV.

Moreover, the term *STATION* represents the charging stations of EVs in each county. Apart from installing charging connectors at home, many EV owners charge their cars at a station rather than their homes, primarily because of its fast-charging capacity. So, this variable should also have a positive relationship with the outcome variable. In my data, I have the opening date of each station or charging connector. Like the *EV* variable, I take the cumulative sum of the number of stations for each county at the monthly level. However, in my model, I primarily use the *STATION* variable and *EV* variable separately as they both should account for the EV adoption. However, I also use these two variables together to see the EV effect while controlling for *STATION* and vice versa.

The remaining variables are control variables. The term *SINGLE* is the percentage of single housing in each county. There are three types of housing available, which are Single, Multi, and Mobile housing. Households with a different number of members may have a different electricity-consuming pattern. People living in the same household can share their electricity services, such as cooking or watching TV together. Thus, if the demand-side economies of scale exist, the effect of different types of households should have different effects on electricity consumption.

HOTMONTH and *COLDMONTH* are two separate variables representing the climate factors, like average hot/cold degree months when people use more electric appliances like air coolers and heaters would positively influence electricity demand. I consider 86 degrees Fahrenheit or more temperature as hot days and 32 Degree Fahrenheit or less as cold days (Alberini et al., 2017). So, if the average monthly temperature is above 86 degrees, the *HOTMONTH* variable would be equal to 1, otherwise 0. Similarly, if the average monthly temperature is below 32 degrees, the *COLDMONTH* variable would be equal to 1, otherwise 0.

The term *PRICE* is the weighted average electricity price of the residential and commercial sectors, which I calculated from electricity consumption and the revenue information. The term *INCOME* is the per capita personal income for each county. Based on the demand theory, the price effect is expected to be negative, while the income effect is expected to be positive on electricity demand. The term POP represents the population for each county, which is the number of potential electricity users. This variable also controls the size of each county. A county with more residences will consume more electricity, so the population's effect would be positive. The variable EMPLOY is the total employment in each county, which controls for any unobserved economic activity for electricity consumption and purchasing EVs.

δ and ϕ stand for county fixed effect and time fixed effect, respectively. More specifically, time fixed effects account for the year- month level in this model.

Renewable Electricity Generation due to EV Adoption

To address the second question of this study, I again employ the two-way fixed-effect model. The electricity from renewable sources in county i and year t would be,

$$RENEWABLE_{it} = b_0 + b_1\, Log(ELECTRIC_{it}) + b_2\, Log(NCOME_{it}) + b_3\, Log(POP_{it}) + \\ b_4\, SINGLE_{it} + b_5\, Log(EMPLOY_{it}) + b_6\, Log(PRICE_{it}) + \delta_t + \phi_i + u_{it} \tag{2}$$

Here, *RENEWABLE* is the percentage share of the electricity generation that comes from renewable sources in a specific county and year. Other variables are the same as the first specification, except the I do not add temperature control here since that should not affect the source of electricity. Electricity generation is supposed to be independent of temperature.

Result

Effect of EV Adoption on Electricity Consumption

Table 2.5 represents the results of the unlogged analysis of the effect of EV adoption on both residential and commercial sectors together. I use a weighted average price for these two sectors. The three separate columns in the table represent different model specifications. In the first column, I use EV as my explanatory variable without the charging station in it. I use the charging station as my explanatory variable without EV in it in the second column. In the third column, I keep both EV and charging station as an explanatory variable. Although charging stations and EVs should be correlated, it is worth looking at the EV effect while controlling for the charging station and vice versa. As we know, least EV adopting counties might also want to build more stations for travelers. This study adopts a two-way fixed-effect model where I control for county-fixed effect and year-month fixed effect. We can see that, in column (2), the charging station has a coefficient of 29.71, and this result is highly significant, which means one extra charging station or connector can increase monthly electricity consumption by 29.71 MWh. In column (3), while accounting for both EV and Station, this coefficient is 27.16. The population has a significant positive result on consumption while Employment has negative impacts. Hot degree months have a highly significant positive effect.

Table 2.5

Effect on Residential & Commercial Consumption

Variables	(1)	(2)	(3)
EV	0.695 (0.447)	×	0.318 (0.701)
Charging Station	×	29.71*** (7.49)	27.16*** (9.93)
Income	0.231 (0.310)	0.819** (0.401)	0.772* (0.412)
Population	0.418*** (0.074)	0.613*** (0.097)	0.608*** (0.098)
Weighted Price	134.74** (55.16)	174.97** (78.68)	171.91** (79.72)
% of Single HH	7,885.49 (720.71)	9,493.09 (7176.01)	10,160.81 (7358.46)
Employment	-0.123*** (0.0431)	-0.297*** (0.056)	-0.308*** (0.059)
Hot Months	169,478.93*** (11725.16)	192,259.71 (13742.45)	191,572.84*** (13843.41)
Cold Months	17,198.96 (12,556.87)	24,458.90 (15,029.43)	25,233.86 (16,430.62)
County Fixed effect	✓	✓	✓
Time Fixed effect	✓	✓	✓

*Notes: *** p<.001, ** p<.01, * p<.05. standard errors reported in parenthesis*
Number of observations = 6960

Table 2.6 shows the logged analysis for several explanatory variables, which represents the primary results of the effect of EV adoption on both residential and commercial sectors together. In this specification all the predictor and the outcome variables are log-transformed. For the weather control, this time, I use numbers of dummy variables with a range of 5° bins for both hot and cold months. I had to drop one of these dummies because none of these months fall under the range of 30-35° Fahrenheit. These weather controls are not logged, as they are binary variables.

Table 2.6

Robustness Check Specifications for Electricity Consumption on EV Adoption

Variable	(1)	(2)	(3)
Log (EV)	0.0062	×	0.0006
	(0.0042)		(0.0079)
Log (Station)	×	0.0105***	0.0118***
		(0.0037)	(0.0039)
Log (Income)	0.0299	0.1909**	0.1536*
	(0.0712)	(0.0847)	(0.0843)
Log (Population)	0.6727***	0.8640***	0.8324***
	(0.1592)	(0.1986)	(0.2056)
Log (Weighted price)	0.0947***	0.1021***	0.0984***
	(0.0142)	(0.0175)	(0.0176)
Log (Employment)	0.1077	0.0831	0.0915
	(0.1055)	(0.1247)	(0.1318)
% of Single HH	0.8180*	1.3947***	0.0195**
	(0.4259)	(0.4580)	(0.0084)
Factor (80-85)	0.1833***	0.1921***	0.1879***
	(0.0128)	(0.0138)	(0.0136)
Factor (>90)	0.4467**	0.4529***	0.4465***
	(0.0358)	(0.0406)	(0.0400)
Factor (25-30)	0.2557***	0.3325***	0.3145***
	(0.0321)	(0.0329)	(0.0363)
Factor (20-24)	0.5465***	0.5751***	0.5781***
	(0.1233)	(0.1181)	(0.1163)
County Fixed Effect	✓	✓	✓
Year Fixed Effect	✓	✓	✓

*Notes: *** p<.001, ** p<.01, p<.05. standard errors reported in parenthesis*
Number of observations = 580

In this specification charging station again shows a significant positive effect on electricity consumption. We can interpret that a 1% increase in charging station installation increases the electricity consumption by 0.012%. According to our average county-level electricity usage data, this 0.012% would yield 33.04 MWh electricity consumption per country per month. This time, single housing unit shows a positive effect. All the temperature variables are positively significant at a 1% level.

Table 2.7 represents the result for the residential electricity consumption only. As before, In the first column, I use EV as my explanatory variable without the charging station in it, and in the second, I use the charging station as my explanatory variable without EV in it. Column (3) shows the result for both EV and charging stations. This model is also a two-way fixed-effect model. In column (2), Station shows a coefficient of 18.22 for residential electricity consumption. This result is significant at a 1% level. So, one extra charging station adoption can cause 18.22 MWh residential electricity consumption monthly. The population has a significant positive result on consumption, employment has a significant negative effect, and hot degree months have a significant positive impact as we expected. In column (3), EV does not have any significant effect, but charging station is still highly significant and has a positive effect on residential electricity consumption.

Table 2.7
Effect on Residential Consumption Only

Variables	(1)	(2)	(3)
EV	0.152 (0.294)	×	-0.179 (0.461)
Charging Station	×	18.22*** (4.92)	20.13*** (6.53)
Income	-0.003 (0.202)	0.279 (0.262)	0.289 (0.269)
Population	0.245*** (0.049)	0.393*** (0.064)	0.392*** (0.064)
Residential Price	7.257 (22.88)	16.16 (32.45)	16.74 (32.77)
Single HH	6,525.89* (3,754.08)	7,330.94 (4,709.09)	6,972.81 (4,828.14)
Employment	-0.058** (0.028)	-0.191*** (0.037)	-0.189*** (0.039)
Hot Months	137,806.95*** (7,707.42)	158,027.64*** (9,029.48)	157,450.91*** (9,093.58)
Cold Months	4,888.51 (8,247.63)	8,853.32 (9,871.24)	9,288.32 (10,790.26)
County Fixed effect	✓	✓	✓
Time Fixed effect	✓	✓	✓

*Notes: *** p<.001, ** p<.01, *p<.05. standard errors reported in parenthesis*
Number of observations = 6960

Electricity Generation in California

Natural gas, coal, nuclear, hydroelectric, solar, and wind are the primary electricity generation sources in California. Among these, hydroelectric, solar, and wind are considered clean, renewable sources. As California State is concerned about the environment and trying to impose public policies to reduce pollutants, it is worth looking at the electricity generation pattern and whether the EV adoption policies are accompanied by more secure and cleaner power plants. To analyze the relationship between EV adoption and renewable energy sources, I construct a variable: the percentage share of electricity that comes from renewable sources in each county. Then, I run a two-way fixed-effect model to see the effect. This time, the data is yearly. So, the time fixed effect represents the year fixed effect. Other variables remain the same.

In California, most renewable electricity comes from hydroelectric power. Solar and wind follow hydroelectricity. There are some biomass and geothermal electricity production as well.

Table 2.8 shows the result of the impact of EV adoption on renewable sources of energy. In the table, column (1), (2), (3), and (4) shows the logged analysis of variables. Column (5) shows the result for unlogged variables. In the first three columns, I use EV and Station as an explanatory variable. However, it seemed more logical to have Electricity itself as the explanatory variable, shown in the column (4), and (5), as high electricity demand or usage should affect the energy mix of the electricity generation decision. According to the U.S. Energy Information Administration, electricity demand is one factor that influences the mix of energy sources for electricity generation. Intermediate load generating units (rather than Baseload units, which supply electricity at a nearly constant rate) comprise the largest generating sector and provide load responsive operation between baseload and peaking service. In general, the demand profile varies over time, and intermediate sources are technically and economically suited for following changes in load. Natural gas-fired combined-cycle units, which currently provide more generation than any other technology, generally operate as intermediate sources.

The result shows that neither EV adoption nor Station increases renewable electricity generation. Instead, when I use Electricity as the explanatory variable, it shows a significant negative impact on renewable energy sources. In this specification, the dependent variable, the percentage of electricity from renewable sources, is not log-transformed, but all the predictor variables are log-transformed. We can interpret that a 1% increase in electricity consumption decreases the renewable energy share by 0.34%. This negative effect is crucial for the policy perspective. It means more EV adoption, or in other words, more electricity usage is accompanied by decreased adoption of renewables sources.

Table 2.8

Effect of Electricity Usage on Renewable Energy Source

	(1)	(2)	(3)	(4)	(5) (Unlogged)
Log (Electric Vehicle)	0.3217 (1.55)	✕	-2.40 (2.89)	✕	✕
Log (Charging Station)	✕	0.5540 (1.51)	0.8954 (1.60)	✕	✕
Log (Electricity)	✕	✕		-34.78 (21.05) *	-0.0000085** (0.0000036)
Log (Population)	-20.12 (61.50)	5.23 (82.50)	-21.30 (85.44)	-9.08 (54.31)	0.000016*** (0.0000036)
Log (Income)	-36.15 (25.35)	-59.65* (32.63)	-68.78** (33.79)	-4.51 (22.66)	0.000022 (0.000015)
Log (Weighted Price)	-1.87 (6.66)	0.9975** (9.81)	0.0235 (9.85)	-0.0906 (5.94)	-0.0055 (0.0039)
Log (Employment)	120.97*** (42.60)	121.81 (51.00)	144.80** (56.02)	139.65 (39.85)	-0.0000024* (0.0000012)
Log (Single HH)	-43.18 (151.93)	-34.87 (178.57)	0.2921 (181.66)	125.79 (148.02)	2.55 (3.01)
County Fixed effect	✓	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓	✓

*Notes: *** p<.001, ** p<.01, p<.05. standard errors reported in parenthesis*
Number of observations = 580

Discussion and Conclusion

In addition to the rebate programs for EV and EVSE, California has enacted several other incentives to adopt electric vehicles, including HOV lane access, zero-emission transit bus tax exemption, and nine other regional incentive programs. The state rebate program for EVs alone has already spent $823 million since 2010 (California Public Utilities Commission, 2020). Nikolewski (2019) provides the breakdown of California's all EV incentive programs' total spending, which is $2.46 billion for approximately ten years. As I stated earlier, all of these incentives have been introduced in response to environmental concerns. In general, experts agree that electric vehicles are cleaner than other conventional vehicles powered by diesel or gasoline while driving because EVs emit fewer pollutants in the atmosphere. Nevertheless, the increased electricity demand due to EV and its supporting infrastructure is an important part of the policy discussions. If this issue is not addressed correctly, there will be unintended consequences on public spending and, most importantly, on the environment. Although California is trying to reduce its coal-based power plants in recent years, coal is still one of its primary electricity sources, along with natural gas and nuclear energy. These power plants emit a significant amount of greenhouse gas and other pollutants, as discussed earlier. Besides, hydroelectricity is the major source of renewable options in California. Solar and wind exist to a limited extent. So, there are rooms for renewable resources to be escalated as one of the primary electricity production sources.

This study has some limitations. California is the biggest importer of electricity as well. In 2018, almost one-third of California's electricity supply came from generating facilities outside the state. In this study, I cannot account for the imported electricity sources, which would be the scope for future research. Another interesting aspect of this research could be analyzing the adoption of small-scale customer-sited solar photovoltaics (PV) in California, known as a behind-the-meter generation, a predominant technology in residential solar PV. In 2019, solar PV self-generated about 16,000 GWh of energy (California Energy Commission, 2019, slide 8). But there is no data available right now at the county level to see the relationship of EV adoption with PV adoption.

However, this study finds that EV adoption significantly increases electricity consumption in residential and commercial sectors, and energy usage is accompanied by a lower adoption of renewable power plants. Considering the average number of charging stations per county, EV adoption increases monthly residential and commercial electricity consumption by 0.012%. Based on California's average energy generation, this would yield 33.04 MWh. Besides, a 1% increase in electricity consumption is associates with 0.34% of the decrease in the renewable electricity share. These results should be an essential viewpoint for policymakers. Evaluating government EV incentives' true environmental impact should weigh the reduced gasoline engine emissions against the increased fossil fuel or nuclear consumption during electricity generation. Unless California adopts cleaner sources of power plants, billions of dollars of public spending on EV adoption will not be as effective as it would be if accompanied by increased adoption of renewable energy sources.

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APPENDICES

APPENDIX C: CLEAN VEHICLE REBATE PROJECT

The Clean Vehicle Rebate Project (CVRP) promotes clean vehicle adoption by offering rebates of up to $7,000 for the purchase or lease of new, eligible zero-emission vehicles, including electric, plug-in hybrid electric, and fuel cell electric vehicles. Until funds are available, eligible California residents can follow a simple process to apply for a CVRP rebate after purchasing or leasing an eligible vehicle. The Center for Sustainable Energy (CSE) administers CVRP throughout the California Air Resources Board (CARB) state. [17] In my dataset, there are a total of 371892 rebate application records.

Income Eligibility

- Income Cap: Higher-income consumers are not eligible for CVRP rebates if their gross annual incomes are above the income cap. The income cap applies to all eligible vehicle types except fuel-cell electric vehicles. The present income cap is mentioned below-
    1. $150,000 for single filers
    2. $204,000 for head–of–household filers
    3. $300,000 for joint filers
- Increased Rebate: Consumers with household incomes less than or equal to 300 percent of the federal poverty level are eligible for an increased rebate amount. Increased rebate amounts are available for fuel-cell electric vehicles, battery electric vehicles, and plug-in hybrid vehicles.

Rebate Limit

Individual and business applicants are not eligible to receive more than one CVRP rebate either via direct purchase and/or lease as of December 3, 2019. Traditional rental and car share fleets are subject to limits of 20 rebates per calendar year. Public fleets are limited to 30 rebates per calendar year.

Vehicle Eligibility

Eligible vehicles must meet requirements that include, but are not limited to, the following:

- Be on the list of Eligible Vehicles which meet required emission standards.
- Be new as defined in the California Vehicle Code (CVC) Section 430 and manufactured by the original equipment manufacturer (OEM) or its authorized licensee. Vehicles considered new vehicles solely for the determination of compliance with state emissions standards are not eligible.
- Be registered as new in California. Vehicles may not be purchased, leased, or delivered out of state. Purchases/leases must be made via a California purchase or lease contract. Vehicles ordered online and delivered outside of California are not eligible. The seller's address, as reflected on the purchase or lease agreement, must be in California.
- Have an odometer reading below 7,500 miles at the time of purchase or lease.

Funding Availability

If funds are not available at the time of application, people may still apply and be placed on a rebate waitlist. Rebates for approved applications on the waitlist will be issued if additional funding from the state of California becomes available.

APPENDIX D: CHARGING STATION REBATE

Rebates for Residential Level 2 Charging Stations

Numbers of California utility providers and air districts[2] offer rebates to make home Level 2 charging stations more affordable. Some of the rebates also help offset the cost of installing the charging station at the EV owner's home if additional electrical work is required. The minimum rebate amount is $400, and the maximum is $4000 based on the location and EVSE type. In California, the most popular charging is Level 2 charging. The median installation cost of a Level-2 charger is $1,200 (Idaho National Laboratory, 2015).

Rebates for Commercial EV Charging Stations

Property owners can get rebates for installing commercial charging stations for public use and thus generate a new revenue stream (charging fees). In California, there are nineteen separate utility incentives and ten air district incentives for the commercial installation of an EV charging station

[2] Air districts refer to county or regional agencies throughout California that have primary responsibility for controlling air pollution from stationary sources and administer various air pollution-related rebate programs and initiatives. California has 23 Air Pollution Control Districts (APCDs) and 12 Air Quality Management Districts (AQMDs).

CHAPTER III

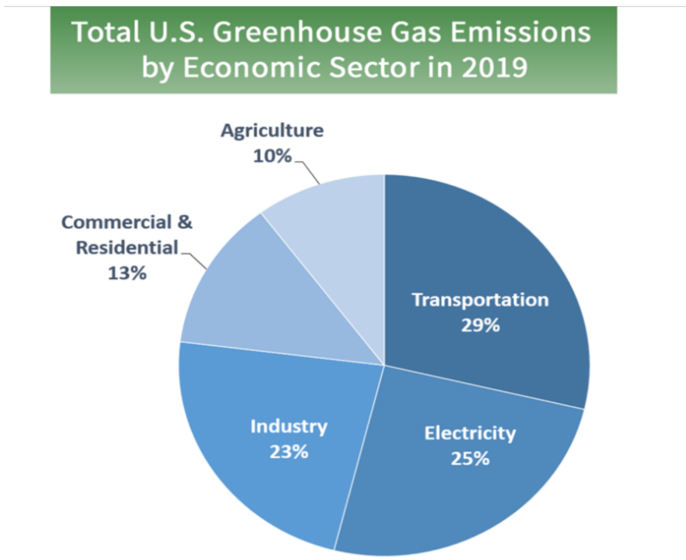
THE FACTORS INFLUENCING THE JOINT ADOPTION OF ELECTRIC VEHICLE AND SOLAR PHOTOVOLTAICS: EVIDENCE FROM CALIFORNIA

Household-level pollution control is certainly an important policy discussion. Along with the government, people are also trying to make greener choices due to climate change concerns. In terms of emission control, there are a number of federal and state-level incentives that are present for electric vehicles (EV). These incentives are making EVs affordable to more consumers, and as a result, EV market share is growing day by day. But, EVs have some other social costs as well. For example, previous study has shown that electric vehicles and their supportive infrastructures, like charging stations, significantly increase residential and commercial electricity consumption in California (Ferdousee, 2021). The study also indicates that the production of electricity is still mostly dependent on non-renewable sources like gasoline and coal. Figure 3.1 shows that, while transportation (29%) is the primary source of greenhouse gas emission in the USA, electricity generation (25%) is the second (EPA 2021). While electricity production is primarily not a household decision, its production certainly depends on household consumption levels in the long run.

Nonetheless, in the USA, people are now interested in getting more renewable energy than before to reduce greenhouse gas production (Borunda, 2021). People are interested in, for example, producing their own energy by installing small-scale photovoltaics or solar power generator. Just like electric vehicles, both federal and state government is incentivizing the solar PVs as well.

Figure 3.1

Total U.S. Greenhouse Gas Emissions by Economic Sector in 2019



Source: US environmental and Protection Agency (2021). Inventory of US greenhouse gas emissions and sinks: 1990-2019.

This study explores the factors that influence the decision to purchase EV as well as installing solar PV at homes in California by implementing a bivariate probit regression model. As both green technologies are new and durable in nature, my hypothesis is that characteristics like education level and age should have a significant impact on making these choices. More specifically, highly educated, younger consumers may have more potential to make these choices. Again, although there are federal and state-level incentives are available, EV is still an expensive option compared to other conventional vehicles. So, the high-income level should have a positive impact on adopting EV. Previous studies also find evidence that age, education, income levels have such effects on adopting these technologies (Nath, 2016; Araújo et al., 2019). Also, different household types should have different effects because of their structures and different energy consumption patterns. However, previous studies that explore the joint adoption of EV and solar applied regression analysis or separate binomial logit or probit model to analyze the factors, whereas this study implements a bivariate probit model to analyze these factors.

The bivariate probit model has the capability to overcome the biases that result from unobserved characteristics of people who are adopting both green technologies. For instance, since EV and solar PV are greener choices, someone who is more environmentally friendly is more likely to have both. An econometrician cannot identify which person is more environmentally friendly from given consumption data. Applying the bivariate probit model, this study strengthens the existing literature on EV and solar PV adoption. The findings suggest income and single household type have a significant positive impact on adopting both. When I consider the future adoption decision, higher education level becomes significant. Moreover, when analyzing the decision to adopt only one technology, we see older age has a negative impact on adopting EV but a positive impact on Solar.

The rest of this study is organized as follows: first, I give a brief literature review in section 2. Section 3 presents an overview of the data and model specification. I offer the results of the analysis in section 4 before concluding in Section 5.

Literature Review

The joint purchase of EV and Solar PV has been discussed in economics literature from several perspectives. Delmas et al. (2016) showed that quality improvements and falling prices of both electric vehicles and solar panels lead to households increasingly purchasing both durable goods as a bundle. They analyzed five years of data of California and concluded that the correlation between the share of households with solar panels and electric vehicles rose over time. For the hypothesis testing, they used the numbers of EV as the dependent variable and the number of solar PV as one of the explanatory variables in the regression analysis.

Nath (2016), in his MA thesis, explored the factors behind the adoption of both EV and solar PV using binomial logit regression and showed that Both EV and solar PV respondents were wealthy and highly educated. A high level of trust is placed upon technology providers and a lower degree of trust in the adopters' interpersonal network. This study also finds strong support for the theory of planned behavior through the identification of the role of personal norms, subjective norms, attitude, and perceived behavioral control on intention and, ultimately, behavior. The mix of environmental, societal, and self-oriented values was clearly observed in the decision-making process.

Araújo et al. (2019) studied electric vehicles and solar photovoltaic technology diffusion in the State of New York. Using geospatial, regression, and cluster analyses of the zip-code level and county indicators, they analyzed trends with locational, political, and socio-demographic profiles to identify areas of convergence and divergence in adoption patterns. Their study confirmed the importance of income and median home value in early-staged, electric vehicle and solar photovoltaic technology adoption. They also found that political orientation and age tendencies are more nuanced and less predictive. However, they noted key adoptive tendencies among those aged 30-44 and above 59 for solar photovoltaics. Moreover, southeastern counties near New York City, particularly on Long Island, are identified as critical niches in the early-staged diffusion of clean energy.

Based on historical diffusion data of solar PV and EV in the Netherlands, Kam et al. (2018) have characterized the adopter groups of these technologies and build scenarios for future diffusion. They also investigate how the joint deployment of these technologies may impact the local energy system and assess the viability of the integration of solar PV and EV in vehicle-to-grid systems. They find large differences in the spatial diffusion patterns of solar PV and EV using 40 regions in the Netherlands, which will have an impact on the viability of vehicle-to-grid systems. To characterize PV and EV adopters, they performed two ordinary least squares (OLS) regressions, one with the number of PV installations per person and one with the number of EVs per person as the dependent variable.

Delmas et al. (2016) argue that the joint purchase of electric vehicles and solar panels is one way to significantly reduce carbon emissions in the suburban United States. This is because electric vehicles may lead to environmental damages due to increasing energy consumption (Graff Zivin et al., 2014; Holland et al., 2015, Ferdousee, 2021). Households that invest in both solar panels and electric vehicles can mitigate their carbon footprint from household and transportation activities.

Unlike the previous studies, this study analyzes the joint purchase decision by using a bivariate probit model. This model can overcome the biases due to some people being more environmentally friendly and consequently being more likely to make more green choices than others.

Data and Methodology

This study uses 2019 California Vehicle survey data from the Transportation Secure Data Center of The National Renewable Energy Laboratory (NREL). From the dataset, I only use the residential portion of the data, which includes 4136 observations. Table 3.1 shows the summary statistics of all the variables. The explanatory variables include age group, education, gender, income, household type, number of household members. This dataset contains geographical information about respondents and divided the state into six separate regions, which will control for region-specific unobservables. Most of the variables are categorical variables, except the number of household members.

Table 3.1

Summary Statistics

Variable	Category	Value
Gender		
	Male	47.78%
	Female	51.06%
	Other	0.15%
	Do not wish to answer	1.02%
Age Group		
	Below 18	0
	18 to 34	12.33%
	35 to 64	52.85%
	65 or above	34.82%
EV		
	Yes	6.67%
	No	93.33%
EV Future		
	Yes	4.3%
	No	95.7%
Solar		
	Yes	15.96%

Table 3.1

Summary Statistics

Variable	Category	Value
	No	84.04%
Solar Future		
	Yes	18.3%
	No	81.7%
Housing		
	Single	76.33%
	Mobile	2.59%
	Multi	20.65%
	Other	0.44%
Education		
	High School	15.21%
	Some College Degree	21.74%
	College Graduate	37.98%
	Postgraduate	25.07%
Income		
	Below 50k	19.15%
	50k – 99.9k	14.7%
	100k - 149.9k	18.74%
	150k - 199.9k	10.28%
	200k - 249.9k	20.79%
	250k or more	7.59%
	Not willing to answer	8.75%
Region		
	Central Valley	5.85%
	Los Angeles	45.21%
	San Diego	7.88%
	San Francisco	9.28%
	Sacramento	23.55%
	Rest of the State	8.15%
	Unknown	0.07%
Total HH Members		
	Min	1
	Mean	2.3
	Max	16
Total sample size is 4136		

There are two binary outcomes of interest. One is having an EV or not having an EV, and another one is having a solar PV or not having a solar PV. People who are more environmentally concerned might be more likely to adopt both. From the data, we cannot identify which respondents are more environmentally friendly. In this case, the bivariate probit model is appropriate for my research question.

The bivariate probit model is a joint model for two binary outcomes. These outcomes may be correlated. If the correlation turns out insignificant, then we can estimate two separate probit models. The unobserved latent variables are presented as:

$$y_1^* = x_1'\beta_1 + e_1 \tag{1}$$

$$y_2^* = x_2'\beta_2 + e_2 \tag{2}$$

In this case, our $x_1 = x_2$

The bivariate probit model specifies the outcomes as:

$$y_1 = \begin{cases} 1 \; if \; y_1^* > \; 0 \\ 0 \; if \; y_1^* \; \leq 0 \end{cases} \tag{3}$$

$$y_2 = \begin{cases} 1 \; if \; y_2^* > \; 0 \\ 0 \; if \; y_2^* \; \leq 0 \end{cases} \tag{4}$$

In this case, y_1 is the binary choice of EV, and y_2 is the binary choice of having a solar PV. The explanatory variables have categorical variables like Education level, Income level, Age Group, Gender, Housing type, and Region. I have one continuous variable, which is the Number of household members. Although California has incentives for both EV and solar, I do not account for that incentive in our model. The reason being these incentives are available statewide, and there is no variation from region to region.

Table 3.2 shows the summary statistics for all variable categories in the percentage level. In this study, EV represents both plug-in-hybrid vehicles and fully battery electric vehicles. In the data, we have information on the future decision of vehicles and solar. So, EV Future and Solar Future variables represent the survey respondents who are interested in purchasing an EV and solar in the future. EV Total and Solar Total variables represent the summation of present and future adoption. Like the present value EV and solar PV analysis, I conduct the same analysis using EV Total and Solar Total when considering both present and future adoption decisions.

Table 3.2

Conditional summary statistics of EV and Solar

Variable	Category	EV	Solar	EV total	Solar Total
Education					
	High School	3.82%	13.83%	34 (5.41%)	177 (28.14%)
	Some College	4.89%	13.79%	9.45%	28.59%
	College Grad	6.17%	15.14%	10.63%	30.55%
	Postgraduate	10.70%	20.35%	15.14%	36.84%
Gender					
	Male	7.99%	17.35%	10.98%	34.06%
	Female	5.35%	14.72%	10.32%	28.88%
	Other	0	1 (16.66%)	0	2 (33.33%)
	Not willing to Answer	11.90%	11.90%	19.04%	26.19%
Income					
	Below 50k	1.91%	8.59%	6.06%	19.82%
	50k – 99.9k	4.11%	15.30%	7.73%	29.61%
	100k - 149.9k	7.23%	16.52%	11.74%	32.90%
	150k - 199.9k	9.88%	20.24%	13.17%	39.76%
	200k - 249.9k	7.20%	13.72%	11.74%	30.00%
	250k or more	15.92%	31.21%	18.15%	50.64%
	Not willing to Ans	7.18%	19.06%	11.88%	32.61%
Region					
	Central Valley	2.89%	14.46%	4.55%	30.58%
	Los Angeles	5.77%	13.74%	9.73%	27.75%
	Rest of the State	5.83%	23.31%	10.74%	38.65%
	San Diego	7.03%	20.83%	10.42%	34.91%
	San Francisco	10.16%	15.21%	15.31%	33.57%
	Sacramento	4.45%	18.99%	7.41%	34.12%
	Unknown	33.33%	0	33.33%	33.33%
Housing					
	Single	7.31%	19.58%	10.64%	37.12%
	Mobile	0	3.73%	4.67%	19.63%
	Multi	5.26%	3.98%	11.82%	11.36%
	Other	0	22.22%	5.56%	33.33%
Age Group					
	18 to 34	7.45%	10.39%	14.12%	27.25%
	35 to 64	7.91%	15.55%	11.71%	32.20%
	65 or older	4.51%	18.54%	7.99%	31.46%

Results

Table 3.3 represents the marginal effects of probit and bivariate probit regression for the present value of adopting EV and Solar. The first two columns show the marginal effects of probit regression for EV adoption and for solar PV adoption separately. Column 3 shows the marginal effect of the bivariate probit model for adopting both technologies. We can see that income has a significant positive effect on adopting both technologies. Single housing type has a positive effect as well. Only postgraduate level education is significant at 1% level. The age group has no significant level in this case.

Table 3.3

Marginal Effects of Present EV- Solar adoption

Variable	Category	Probit EV	Probit Solar	Biprobit EV- Solar
Education				
	High School	----	-----	-----
	Some College	.0101	-.0092	.0020
		(0.421)	(0.614)	(0.593)
	College Grad	.0141	.0053	.0047
		(0.212)	(0.757)	(0.186)
	Postgrad	.0432	.0303	.0149**
		(0.001)	(0.111)	(0.001)
Gender				
	Male	-----	-----	-----
	Female	-.0231**	-.02132	-.0085**
		(0.003)	(0.055)	(0.001)
	Other	N E	.0278	-.0263***
			(0.866)	(0.000)
	Not willing to Answer	.0408	-.0270	.0072
		(0.417)	(0.622)	(0.653)
Income				
	Below 50k	-----	-----	-----
	50k – 99.9k	.0159	.0325	.0057
		(0.154)	(0.082)	(0.063)
	100k - 149.9k	.0417***	.0445*	.0133***
		(0.000)	(0.014)	(0.000)

Table 3.3

Marginal Effects of Present EV- Solar adoption

Variable	Category	Probit EV	Probit Solar	Biprobit EV- Solar
	150k - 199.9k	.0597***	.0719**	.0215***
		(0.00)	(0.001)	(0.000)
	200k - 249.9k	.0446***	.0225	.0116***
		(0.000)	0.186)	(0.000)
	250k or more	.0947***	.1541***	.0442***
		(0.000)	(0.000)	(0.000)
	Not willing to Answer	.0428**	.0725**	.0164**
		(0.006)	(0.002)	(0.001)
Age Group				
	18 to 34	-----	-----	-----
	35 to 64	-.0125	.0281	.0005
		(0.386)	(0.088)	(0.893)
	65 or older	-.0381*	.07632***	-.0027
		(0.010)	(0.000)	(0.540)
Region				
	Central Valley	-.0391	-.0883**	-.0189*
		(0.066)	(0.007)	(0.021)
	Los Angeles	-.0165	-.1041***	-.01397*
		(0.339)	(0.000)	(0.047)
	Rest of the State	-----	-----	-----
	San Diego	-.0028	-.0351	-.0029
		(0.895)	(0.259)	(0.740)
	San Francisco	.0133	-.1074***	-.0069
		(0.476)	(0.000)	(0.345)
	Sacramento	-.0320	-.0696*	-.0154
		(0.109)	(0.023)	(0.053)
	Unknown	.2102	NE	-.0326
		(0.379)		(0.000)
Housing				
	Single	.0159	.1269***	.0168***
		(0.102)	(0.000)	(0.000)
	Mobile	N E	-.0163	-.0086***
			(0.471)	(0.000)
	Multi	-----	-----	-----
	Other	NE	.2042	-.0086***
			(0.054)	(0.000)
HH member		.0036	.0257***	.0037**
		(0.311)	(0.000)	(0.002)
				Rho=.2674
				athrho=.2741
*NE= Not Estimable				(000)

*Notes: *** p<.001, ** p<.01, * p<.05. p values reported in parenthesis*

The correlation coefficient of Present EV-Solar adoption is 0.2674, and it is significant, which suggests that the bivariate probit model is appropriate here rather than two separate probit models. The result shows that increasing fifty-thousand-dollar income above a hundred thousand can increase the probability of adopting EV and solar PV together by 1% to 4%. Being a part of a single household increases the probability by 1%.

Table 3.4 shows the marginal effect of the bivariate probit model for adopting either EV or Solar PV. We can see that Income is more significant for EV adoption than Solar, which is expected because although the State gives incentives for EV, it is still an expensive choice for consumers. 65 or older age group is highly significant in adopting only solar. This group is also significant at a 1% level for adopting the only EV. My result resonates with Araújo et al. (2019) that age group tendencies are more nuanced and less predictive.

Table 3.4

Marginal effect of Bivariate Probit for adopting either EV or Solar

Variable	Category	Only EV, No Solar	Only Solar, No EV
Education			
	High School	----	-----
	Some College	.0080	-.0107
		(0.362)	(0.526)
	College Grad	.0099	.0019
		(0.207)	(0.904)
	Postgrad	.0264**	.0148
		(0.003)	(0.389)
Gender			
	Male	-----	-----
	Female	-.0137*	-.01328
		(0.012)	(0.184)
	Other	-.0512***	.0535
		(0.000)	(0.745)
	Not willing to Answer	.0368	-.03456
		(0.342)	(0.443)
Income			
	Below 50k	-----	-----
	50k – 99.9k	.0097	.02606
		(0.231)	(0.140)
	100k - 149.9k	.0272**	.0300
		(0.001)	(0.076)
	150k - 199.9k	.0375**	.0497*
		(0.001)	(0.015)
	200k - 249.9k	.0312***	.01015
		(0.000)	(0.521)
	250k or more	.0493***	.1103***
		(0.000)	(0.000)
	Not willing to Answer	.0250	.0554*
		(0.020)	(0.011)
Age Group			
	18 to 34	-----	-----
	35 to 64	-.0136	.0270
		(0.210)	(0.055)
	65 or older	-.0354**	.07813***
		(0.001)	(0.000)
Region			
	Central Valley	-.01513	-.0673*
		(0.245)	(0.028)
	Los Angeles	.00133	-.0884***
		(0.896)	(0.000)
	Rest of the State	-----	-----
	San Diego	.00413	-.0314
		(0.743)	(0.269)

Table 3.4

Marginal effect of Bivariate Probit for adopting either EV or Solar

Variable	Category	Only EV, No Solar	Only Solar, No EV
	San Francisco	.0237*	-.0993***
		(0.038)	(0.000)
	Sacramento	-.0114	-.0524
		(0.340)	(0.064)
	Unknown	.2408	-.2127***
		(0.298)	(0.000)
Housing			
	Single	-.00214	.1094***
		(0.795)	(0.000)
	Mobile	-.0476***	-.0083
		(0.000)	(0.709)
	Multi	-----	-----
	Other	-.0476***	.2126
		(0.000)	(0.045)
HH member		.00002*	.0222***
		(0.01)	(0.000)

*Notes: *** p<.001, ** p<.01, * p<.05. p values reported in parenthesis*

Besides analyzing the present factors of EV and solar adoption, I am also interested in analyzing the future decision of people about these two technologies. In the dataset, there were survey questions about the future decision of their vehicle choice as well as about having a solar. Based on the responses, I create variables on future EV and solar, then run a similar analysis. In this case, I consider both present and future EV and solar purchaser and sum them up to construct new dependent variables, which are EV Total and Solar Total. Table 3.5 shows the marginal effect of this analysis for probit and bivariate probit model. In this case, again, the correlation coefficient indicates that bivariate probit is more appropriate, which is represented by the third column of the table. In this case, education level has a more significant effect than the present analysis for adopting EV and Solar. College degrees increases the probability by around 2%, and postgraduate degree can increase the possibility by around 4%. Income level and single housing have a significant positive effect as before. In this case, the 65 years or older age group shows a significant negative impact of adopting these technologies. This age group decreases the probability of joint adoption by 2%.

Table 3.5

Total EV Solar Average Marginal Effect

		Probit EV_total	Probit Solar_total	Biprobit EV_total- Solar_total
Education				
	High School	----	-----	-----
	Some College	.04319**	.0072	.01683**
		(0.003)	(0.754)	(0.005)
	College Grad	.04216**	.0250	.01847**
		(0.001)	(0.237)	(0.001)
	Postgrad	.0756***	.0534	.03538***
		(0.000)	(0.022)	(0.000)
Gender				
	Male	----	-----	-----
	Female	-.0002	-.0462**	-.00539
		(0.978)	(0.001)	(0.200)
	Other	0	.03847	-.04799***
			(0.838)	(0.000)
	Not willing to Ans	.0729	-.0524	.0195
		(0.209)	(0.441)	(0.434)
Income				
	Below 50k	----	-----	-----
	50k – 99.9k	.0070	.04034	.0058
		(0.639)	(0.098)	(0.312)
	100k - 149.9k	.04204**	.0653**	.02135**
		(0.007)	(0.006)	(0.001)
	150k - 199.9k	.0487*	.1173***	.0307***
		(0.010)	(0.000)	(0.000)
	200k - 249.9k	.0456**	.0475*	.0205***
		(0.002)	(0.035)	(0.000)
	250k or more	.0802**	.1791***	.0542***
		(0.001)	(0.000)	(0.000)
	Not willing to Ans	.04009*	.0729*	.0220***
		(0.039)	(0.013)	(0.007)
Age Group				
	18 to 34	----	-----	-----
	35 to 64	-.03397	.0116	-.01095
		(0.052)	(0.601)	(0.146)

Table 3.5

Total EV Solar Average Marginal Effect

		Probit EV_total	Probit Solar_total	Biprobit EV_total- Solar_total
	65 or older	-.0679*** (0.000)	.0376 (0.121)	-.02186** (0.006)
Region				
	Central Valley	-.0735** (0.003)	-.0871* (0.024)	-.0400** (0.001)
	Los Angeles	-.02836 (0.167)	-.1155*** (0.000)	-.0250* (0.016)
	Rest of the State	----	-----	-----
	San Diego	-.02264 (0.359)	-.0413 (0.239)	-.0049 (0.656)
	San Francisco	.01349 (0.546)	-.0827** (0.006)	-.0302* (0.011)
	Sacramento	-.05069* (0.036)	-.0789* (0.025)	-.03017 (0.011)
	Unknown	.1745 (0.496)	-.0769 (0.749)	.0517 (0.680)
Housing				
	Single	-.0074 (0.561)	.2112*** (0.000)	.0253*** (0.000)
	Mobile	-.0362 (0.260)	.0990* (0.030)	.0025 (0.825)
	Multi	----	-----	-----
	Other	-.0542 (0.358)	.2443* (0.035)	.0056 (0.855)
HH member		-.0035 (0.422)	.0503*** (0.000)	.0046 (0.015)
				rho= .1674 athrho= .1689 (0.000)

*Notes: *** p<.001, ** p<.01, * p<.05. p values reported in parenthesis*

Table 3.6 shows the marginal effect of the bivariate probit model of having either EV or solar PV. In this case, Education is significant for having the only EV; income level becomes less significant in than present analysis. More household members have a positive impact on adopting only solar.

Table 3.6

Marginal effect of Bivariate Probit for adopting either EV or Solar

Variable	Category	Only EV, No Solar	Only Solar, No EV
Education	High School	----	-----
	Some College	.0262**	-.0092
		(0.004)	(0.665)
	College Grad	.0238**	.0061
		(0.003)	(0.757)
	Postgrad	.0399***	.0175
		(0.000)	(0.418)
Gender	Male	-----	-----
	Female	.0054	-.0405
		(0.358)	(0.001)
	Other	-.0585***	.0867
		(0.000)	(0.645)
	Not willing to Ans	.0528	-.0699
		(0.177)	(0.215)
Income	Below 50k	-----	-----
	50k – 99.9k	.0010	.0342
		(0.919)	(0.130)
	100k - 149.9k	.0201	.0434*
		(0.048)	(0.044)
	150k - 199.9k	.0178	.0857**
		(0.129)	(0.001)
	200k - 249.9k	.0248*	.0264
		(0.014)	(0.200)
	250k or more	.0261	.1246***
		(0.053)	(0.000)
	Not willing to Ans	.0188	.0502
		(0.132)	(0.059)
Age Group	18 to 34	-----	-----
	35 to 64	-.0234*	.0228
		(0.041)	(0.233)
	65 or older	-.0465***	.0597**
		(0.000)	(0.005)
Region	Central Valley	-.0313	-.0430
		(0.023)	(0.138)
	Los Angeles	-.0016	.0469
		(0.884)	(0.194)
	Rest of the State	-----	-----
	San Diego	-.0061	.0204
		(0.651)	(0.560)
	San Francisco	.0203	-.0303
		(0.104)	(0.320)
	Sacramento	-.0187	-.0018
		(0.165)	(0.959)
	Unknown	.1174	-.0860

Table 3.6

Marginal effect of Bivariate Probit for adopting either EV or Solar

Variable	Category	Only EV, No Solar	Only Solar, No EV
		(0.510)	(0.637)
Housing	Single	-.0332**	-.0894*
		(0.001)	(0.030)
	Mobile	-.0387	-.1856***
		(0.081)	(0.000)
	Multi	-----	-----
	Other	-.0611	.0518
		(0.045)	(0.640)
HH member		-.0079**	.0456***
		(0.003)	(0.000)

*Notes: *** p<.001, ** p<.01, * p<.05. p values reported in parenthesis*

Lastly, I try to predict future solar adoption possibilities with the present adoption of EV and vice versa. More specifically, I am interested to see if EV ownership influences solar adoption. As I stated earlier, EVs require electricity for charging, increasing household energy consumption at a significant level (Ferdousee, 2021). A consumer might be interested in adopting solar PV to cut down the effect. So, EV ownership might impact the decision to have a solar. The opposite could also be true. In this case, EV (and solar) becomes an explanatory variable. In this probit regression, Table 3.7 shows that EV has a positive impact on solar, which is significant at 5% level, but solar has no significant impact on EV. EV adoption increases the possibility of having a solar PV by 7%.

Table 3.7

Marginal Effect of predicting One with Another: Probit Model

		Predicting Future Solar	Predicting Future EV
EV present		.0773*	-----
		(0.014)	
Solar Present		-----	-.0100
			(0.242)
Education			
	High School	-----	-----
	Some College	.0184	.0312***
		(0.372)	(0.000)
	College Grad	.0260	.0307***
		(0.169)	(0.000)
	Postgrad	.0378	.0344***
		(0.076)	(0.000)
Gender			
	Male	-----	-----
	Female	-.0335*	.0213**
		(0.010)	(0.001)
	Other	.0119	NE
		(0.947)	
	Not willing to Ans	-.0341	.0298
		(0.572)	(0.403)
Income			
	Below 50k	-----	-----
	50k – 99.9k	.0164	-.0025
		(0.455)	(0.813)
	100k - 149.9k	.0317	.0116
		(0.139)	(0.295)
	150k - 199.9k	.0686*	-.0039
		(0.011)	(0.694)
	200k - 249.9k	.0326	.0096
		(0.112)	(0.362)
	250k or more	.0636***	-.0186
		(0.046)	(0.109)
	Not willing to Ans	.0127*	.0058
		(0.629)	(0.656)
Age Group			
	18 to 34	-----	-----
	35 to 64	-.0117	-.0255
		(0.571)	(0.035)
	65 or older	-.0235	-.0350**
		(0.296)	(0.005)
Region			
	Central Valley	-.0288	-.0289

Table 3.7

Marginal Effect of predicting One with Another: Probit Model

		Predicting Future Solar	Predicting Future EV
		(0.431)	(0.066)
	Los Angeles	-.0482***	-.0105
		(0.078)	(0.491)
	Rest of the State	-----	-----
	San Diego	-.0259	-.0189
		(0.445)	(0.215)
	San Francisco	-.0113**	.0050
		(0.701)	(0.730)
	Sacramento	-.0393*	-.0194
		(0.244)	(0,216)
	Unknown	.0539	NE
		(0.818)	
Housing			
	Single	.1218***	-.0192*
		(0.000)	(0.031)
	Mobile	.1263**	-.0046
		(0.005)	(0.853)
	Multi	-----	-----
	Other	.0921	-.0096
		(0.390)	(0.845)
HH member		.0356***	-.0056
		(0.000)	(0.071)

*Notes: *** p<.001, ** p<.01, * p<.05. p values reported in parenthesis*

*NE= Not Estimable

Conclusion

Although several previous studies explore the joint adoption of EV and solar PV, this study distinctively implemented a bivariate probit model to analyze these factors. This model enables us to overcome the biases due to unobservable characteristics like environmental friendliness driving both decisions. This study strengthens the existing literature on EV and solar PV adoption by applying the bivariate probit model.

The findings of this study are consistent with previous literature in that income plays a significant role in adopting both EV and solar PV. Higher levels of education are highly significant when I consider the future decision. In this case, the age group of 65 years or older shows a significant negative impact. Again, this age group shows a positive impact when I consider only solar adoption. Moreover, single household types are more likely to adopt EV and solar PV together. Although EV and solar PV incentives are available statewide, the central valley area shows a significant negative effect on this adoption, which should be a concern for the local governments.

Since electric vehicles significantly increase energy usage, it was one of my interests to see if adopting EV impacts adopting solar in the future. However, I find a lower significant positive effect on that. I find no significant effect for the opposite relationship, i.e., that solar panels do not impact EV adoption. So, there might be greater externalities to subsidizing EV rather than solar. If policymakers care about joint adoption, this relationship is something they should consider.

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