The Effect of Tax Credit Policy on Electric Vehicle Sales:

A Synthetic Control Approach using Bayesian Structural Time Series

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ABSTRACT

The government is intervening in automobile markets to reduce greenhouse gas emissions in many places. Several tax incentive programs, both federal and state level, are being effective for environment-friendly vehicles over the past few years. Previous studies focused on discrete choice models analyzing such policies. In this study, however, I employed a Bayesian structural forecasting model to construct a synthetic control to test the effects of state-level tax credit policy in Maryland using a unique time-series data set of vehicle sales record. I observed a significant positive policy effect on electric vehicle sales.

Keywords: Tax credit policy, Bayesian structural time series model, electric vehicle, synthetic control

1 INTRODUCTION

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 emission; notably, Norway by 2025, China by 2030, India by 2030, Germany by 2030, France by 2040, and Britain by 2040 or 2050 (Riley, 2017), (Fingas, 2016), (Petroff, Alanna). 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. The plug-in car market is also going to shift towards fully electric battery vehicles gradually. Most recently, in July 2019, US-based Motor Trend Automotive Magazine awarded an electric car as "ultimate car of the year" (Guarnieri, 2012). Compared with internal combustion engine cars, electric vehicles are quieter, have no tailpipe emissions, and lower emissions in general.

Several national and local governments have established government incentives for plug-in hybrids and electric vehicles, like tax credits, subsidies, etc. 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 $7,500 per car (Alternative Fuel Data Center [AFDC], 2019). Prior studies have tested these policies 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 our analysis in section 5. Finally, I put some robustness checking and sensitivity analysis in section 6 before concluding in section 7, along with some discussions about the limitation and scope of this study.

2 LITERATURE REVIEW

Østli, Fridstrøm, Johansen, and Tseng (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 approval rate of CO_2 emissions from new passenger cars registered in Norway. The fuel tax 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 cars. This paper formalizes a general dynamic discrete choice framework in which forward-looking agents optimize their utility over time; two options are available 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, 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. Bolduc, Boucher, Daziano (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 integral 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 following article titled "Inferring causal Impact using Bayesian structural time series model," 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.

3 OVERVIEWS OF POLICY & DATA

3.1 Maryland Tax Credit Program

Apart from federal incentives, Maryland is offering a one-time excise tax credit 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 be 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 the 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 MD or consumers from other applicable states might be applying for 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 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, 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).

3.2 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).

TABLE 1 — Descriptive Statistics for Pre and 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		

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.

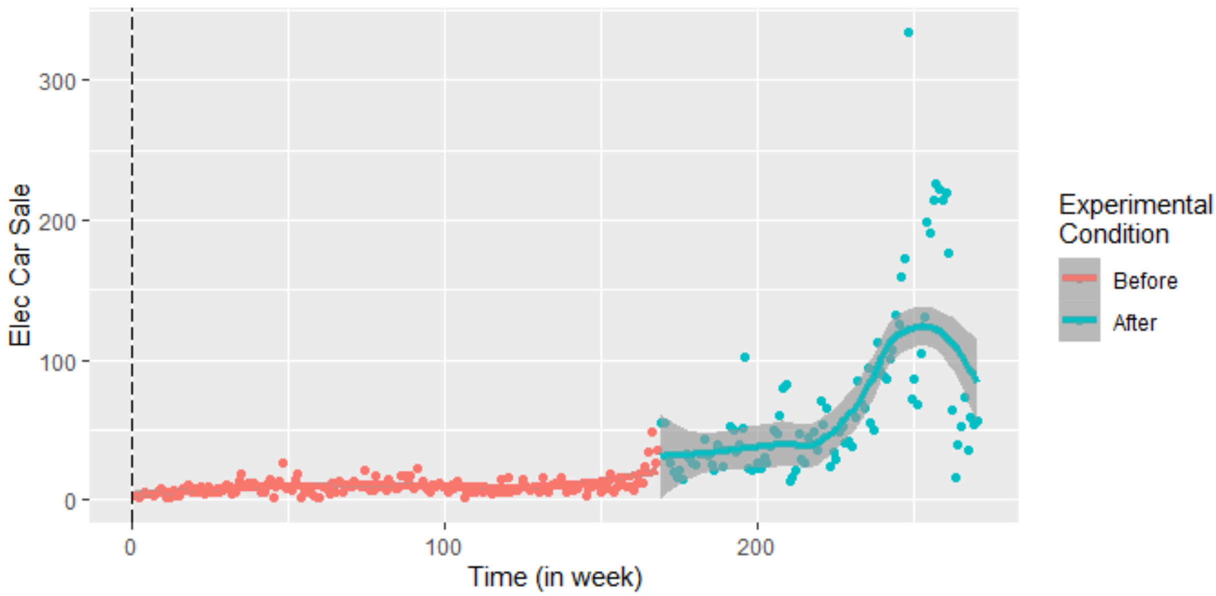

Figure 1 Electric vehicle sales before and after the tax credit policy. Red and blue lines are smoother for the dotted plots.

Figure 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.

However, national-level sales data[1] shows a steady trend for EV over the past few years except for 2015. Although EV market share is small in comparison with our total vehicle

[1] Source: evadoption.com and greentechmedia.com

sales record, in most recent years, EV sales increased at a noticeable rate where total vehicle sales rather decreased over this period (see Figure 3).

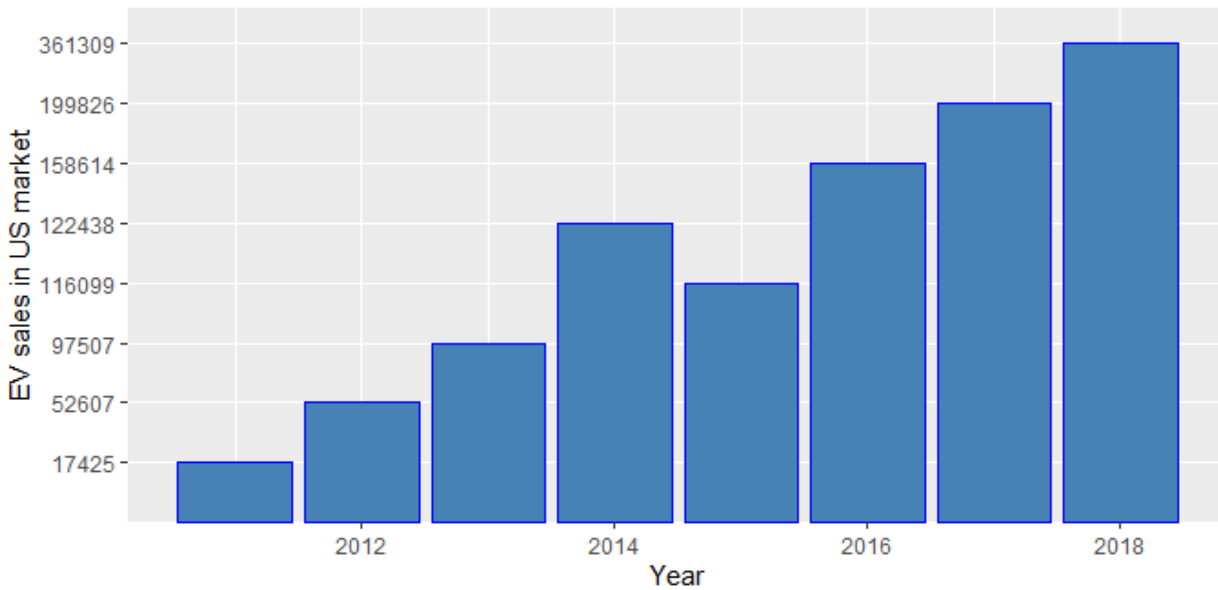

Figure 2 Total electric vehicle sales in the US market over the past eight years. Sales increased at a steady rate except for a decrease in 2015.

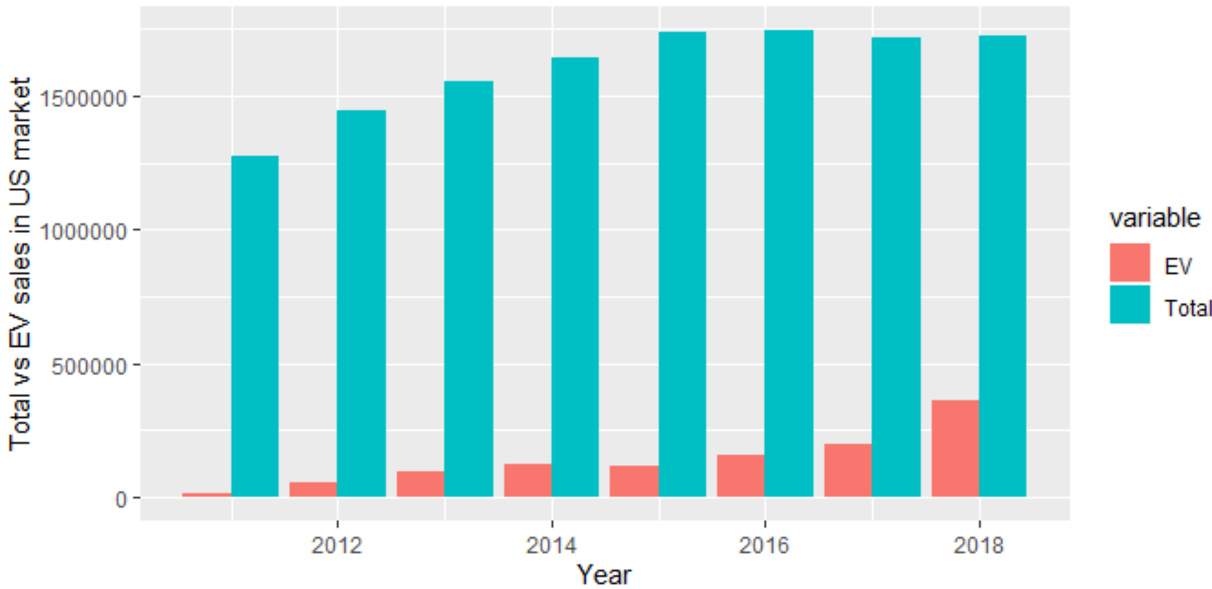

Figure 3: Total electric vehicle sales in comparison with total light-duty vehicle sales in the US market for the year 2011-2018[2]. After 2015, total sales slightly decreased, but EV sales increased at a faster rate.

4 THEORETICAL BACKGROUND & MODEL SPECIFICATIONS

4.1 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

[2] In 2018, the U.S. auto industry sold about 17.2 million light vehicle units. Figure 3 includes the retail sales of 5.3 million autos and 11.9 million light truck units.
Note. I scaled the total sales by dividing its value with 10 to make this bar plot more visually convenient.

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.

4.2 Bayesian Structural Time-Series Models

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

$$(1) \quad y_t = Z^T_t \alpha_t + \varepsilon_t$$

$$(2) \quad \alpha_{t+1} = T_t \alpha_t + R_t \eta_t$$

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:

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

In the present case, response variable is EV sales in 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 of as the region of firmest subjective belief, within which an unobserved parameter falls (Jaynes & Kempthorne, 1976).

4.3 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-

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

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

$$\gamma_{t+1} = -\sum_{s=0}^{S-1}(\gamma_{t-s} + \eta_{\delta,t})$$

Where S represents the number of seasons, and γ_t 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+1} 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,

$$-1 \times (\text{winter} + \text{summer} + \text{fall})$$

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.

In Appendix B, I discuss more about how I select the state components.

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.

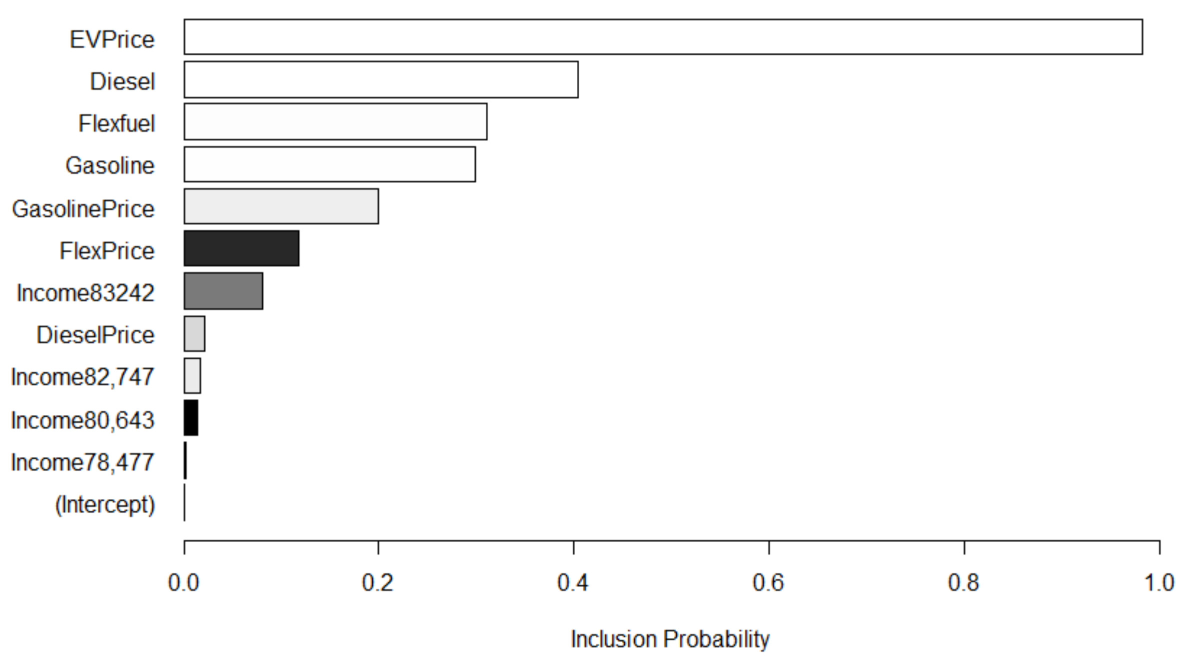

Figure 4: Inclusion probability of all the covariates for the BSTS model. A white bar indicates that the predictor has a positive relationship with consumer sentiment, and a black bar indicates a

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. Figure 4 shows the inclusion probability of the covariates of our model. All covariates are assumed to be contemporaneous.

4.4 Prior Distributions and Prior Elicitation

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

$$\boldsymbol{\theta}\text{: } \{\sigma_u^2, \sigma_\delta^2, \boldsymbol{\beta}\}$$

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 $p(\theta)$ 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 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.

4.5 Inference

Posterior inference in this model can be broken down into three pieces.

First, I simulate draws of the model parameters θ 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.

Posterior Predictive Simulation:

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

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

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.

4.6 Causal Impact

After selecting the best fit BSTS model (see appendix B), 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, . . . , m, we set,

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

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-

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

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

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.

5 RESULT

Table 2 presents the results of the BSTS analysis, and Figure 5 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 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.

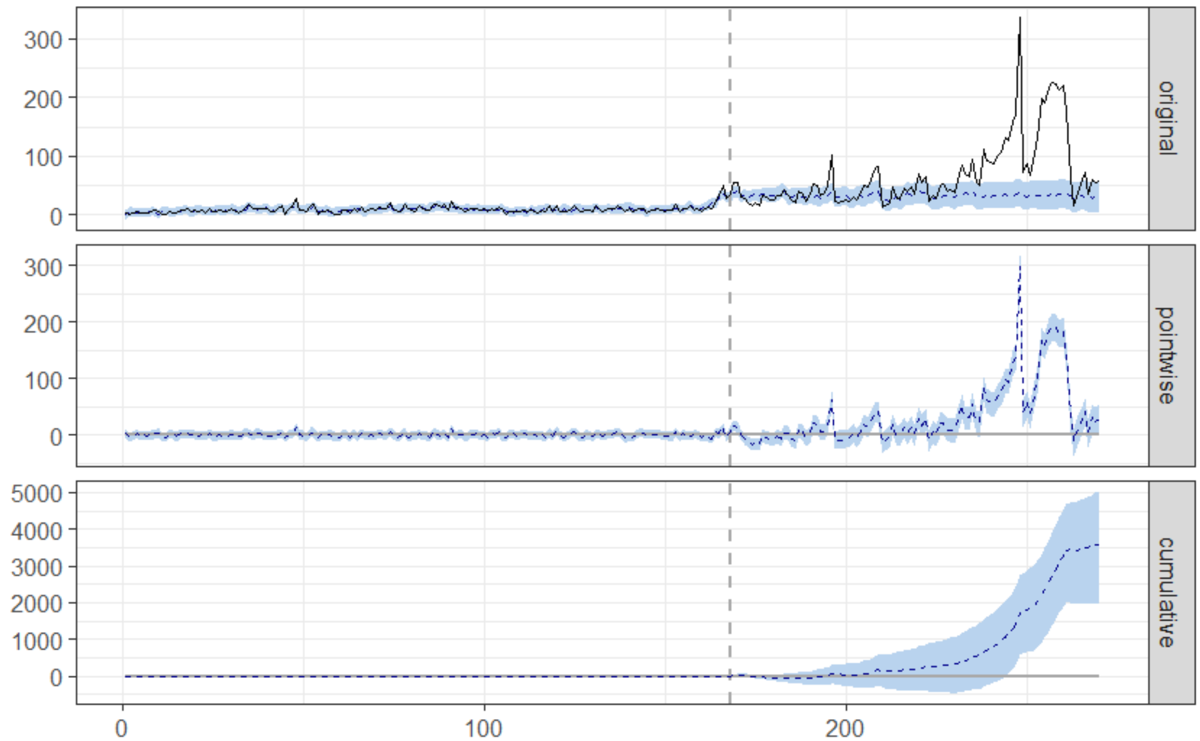

Figure 5 Electric vehicle sales before and after the tax credit program. The upper plots ("original") show the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% credible interval, according to the Bayesian structural time series model. The 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.

6 ROBUSTNESS CHECK

6.1 Percentage Change in EV Sales

To see the percentage change in sales of Electric vehicles, I repeat the process for logged dependent variable along with respective logged covariates. Table 3 shows the results of the BSTS analysis. Figure 6 visualize observed and predicted time series data.

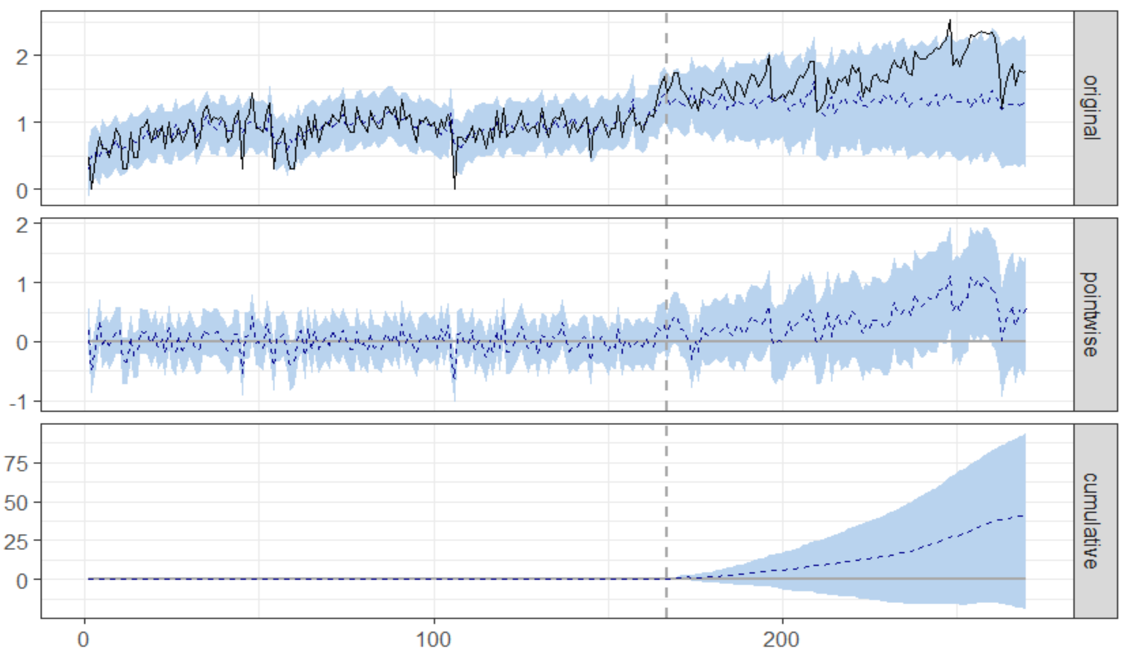

Figure 6 Percentage change in electric vehicle sales before and after the tax credit program.

TABLE 3— Causal Effect Analysis for the Percentage Change in Variables

		Actual Effect	*Predicted*	*Predicted Lower-Upper*	*SD*
Actual	Average	1.7	174.6	[.83- 2]	0.29
	Cumulative	1.4	141.1	[84.29- 203]	29.82
		Absolute Effect	*Absolute Lower*	*Absolute Upper*	*SD*
Absolute	Average	0.33	-0.28	0.89	0.29
	Cumulative	33.56	-.2869	90.33	29.82
		Relative Effect	*Relative Lower*	*Relative Upper*	*SD*
Relative		24%	-20%	64%	21%
Posterior tail area probability, P=0.12028					
Posterior probability of a causal effect: 88%					

Result suggests that, although the intervention appears to have caused a positive effect, this effect is not statistically significant when considering the entire post-intervention period as a whole. Individual days or shorter stretches within the intervention period may still have had a significant effect, as indicated whenever the lower limit of the impact time series (lower plot) was above zero.

6.2 Causal Impact on Other Fuel Type Vehicles

Table 4 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. Figure 7 visualizes the observed and predicted time-series data for other fuel type vehicles combined. In this case, we clearly find no policy effect during the post-intervention period.

TABLE 4—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%

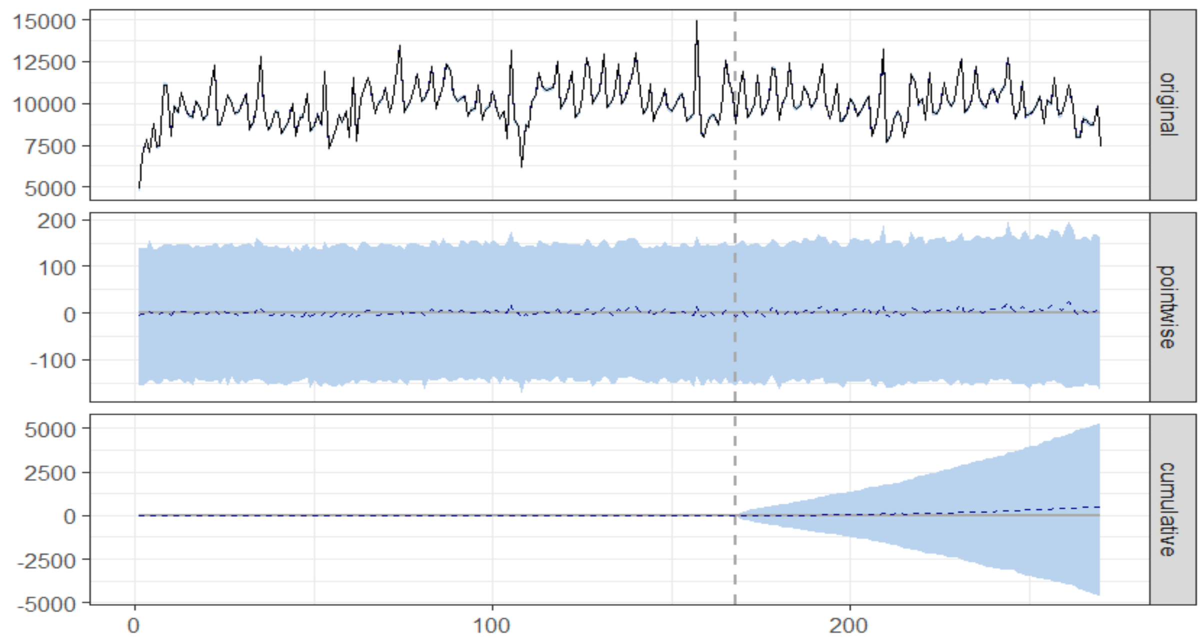

Figure 7 Sales for other types of vehicles combined before and after ax credit program. No increase in sales after the policy implemented. The plot shows the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% credible interval (blue area), according to the Bayesian structural time series model.

Figure 8, which depicts the BSTS analysis for diesel vehicles, also shows no policy effect whatsoever. Figure 9, on the contrary, shows a slight increase in sales for gasoline vehicles after the policy was implemented. But p value= 0.12553 of this analysis suggests that the effect is spurious and thus would not be considered statistically significan

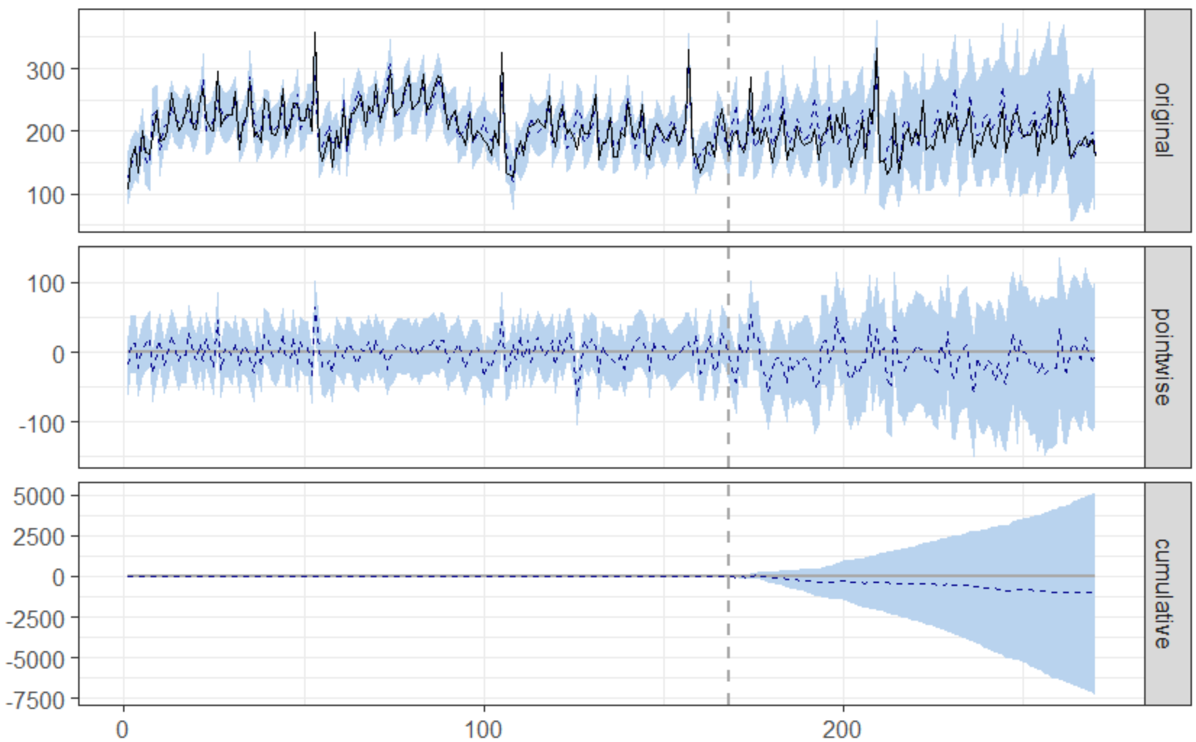

Figure 8 The diesel car sale before and after the tax credit program. No increase in sales after the policy implemented. The plot shows the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% credible interval, according to the Bayesian structural time series model.

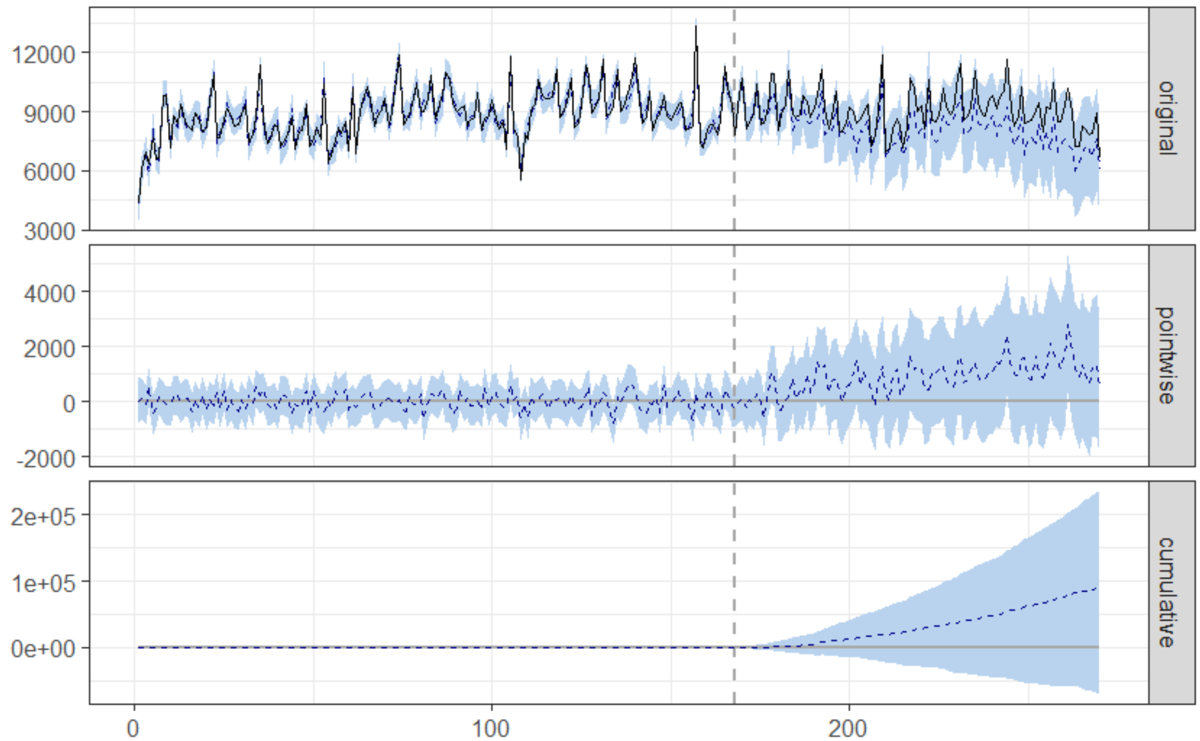

Figure 9 The gasoline car sale before and after the tax credit program. No increase in sales after the policy implemented. The plot shows the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% confidence interval, according to the Bayesian structural time series model.

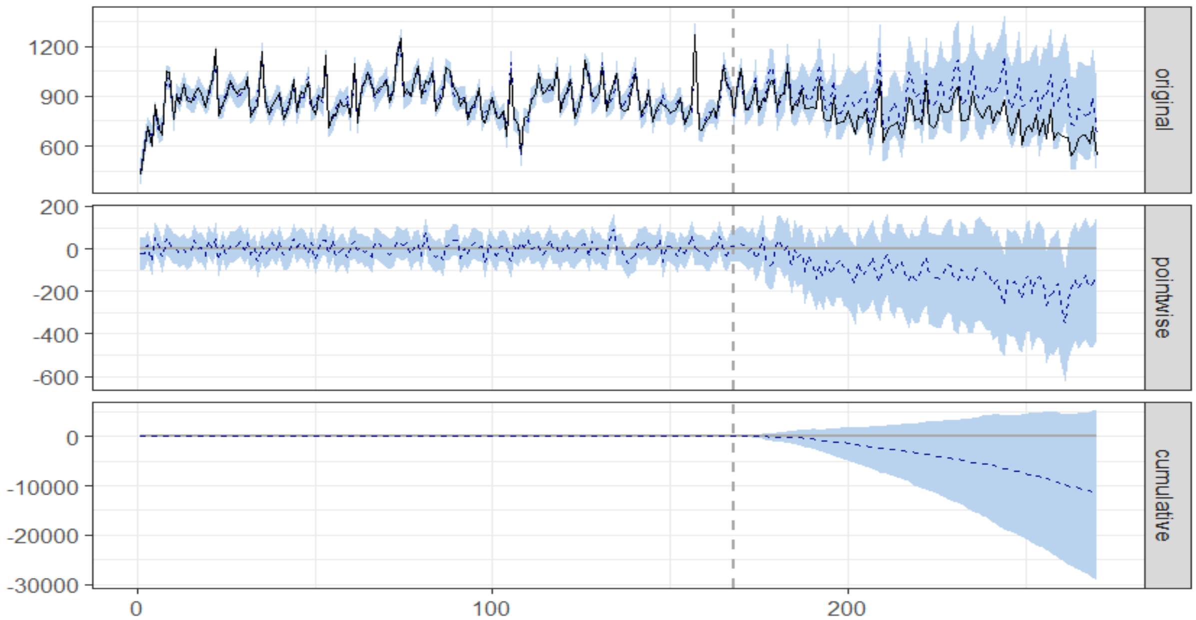

Figure 10 The flex-fuel car sale before and after the tax credit program. No increase in sales after the policy implemented. The plot shows the observed sales (solid black line) and the counterfactual synthetic controls (dashed blue line), including the 95% confidence interval, according to the Bayesian structural time series model.

However, the analysis of flex-fuel vehicles shows a decrease in sales after the tax credit program in Figure 10. This effect is -110.66 with a 95% interval of [-284.37, 50.66]. But again, the probability of obtaining this effect by chance is p = 0.077, which means the effect may be spurious and would generally not be considered statistically significant.

6.3 Sales Pattern:

Figure 11 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 12 shows the relationship of EV with other fuel type vehicle sales over time.

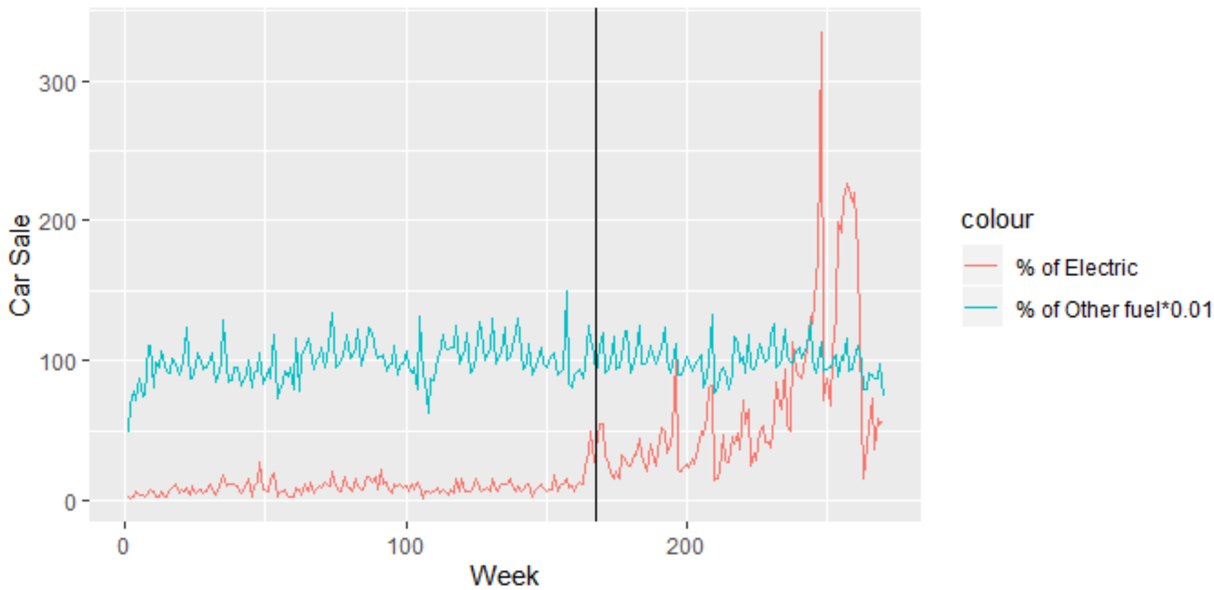

Figure 11 Plots of electric vehicles and other fuel type vehicles over time for comparison. I scaled the other fuel type vehicle sales by dividing the number with 100 for better visual representation. The black vertical line represents the intervention point.

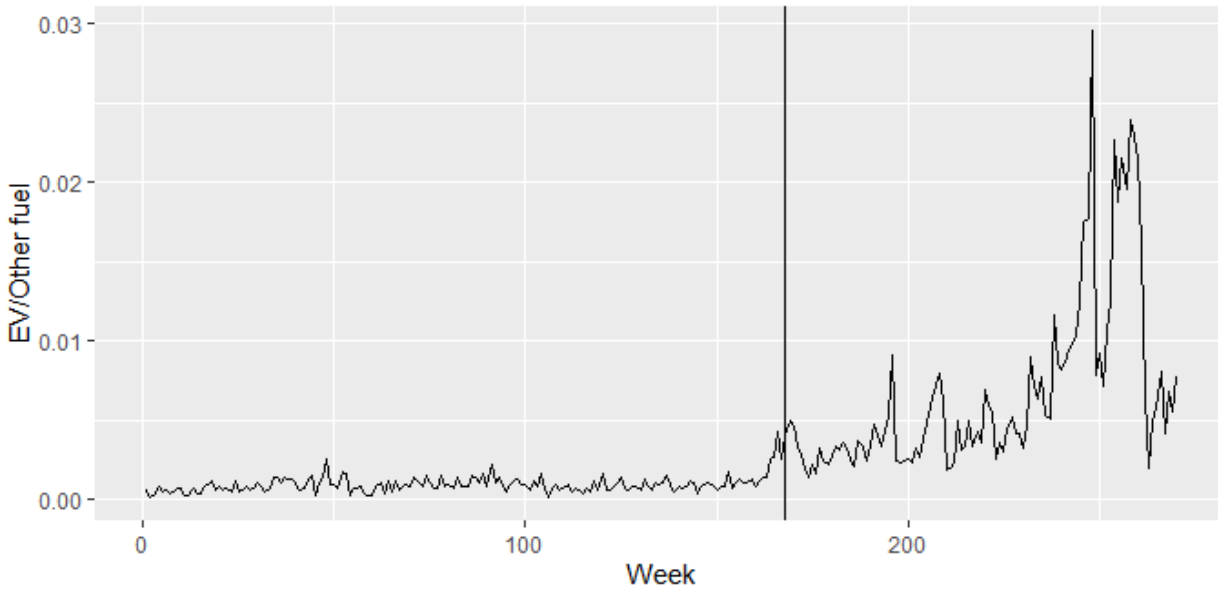

Figure 12 The ratio of EV sales with other fuel type sales during our Pre-period and Post period.

6.4 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 13 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.

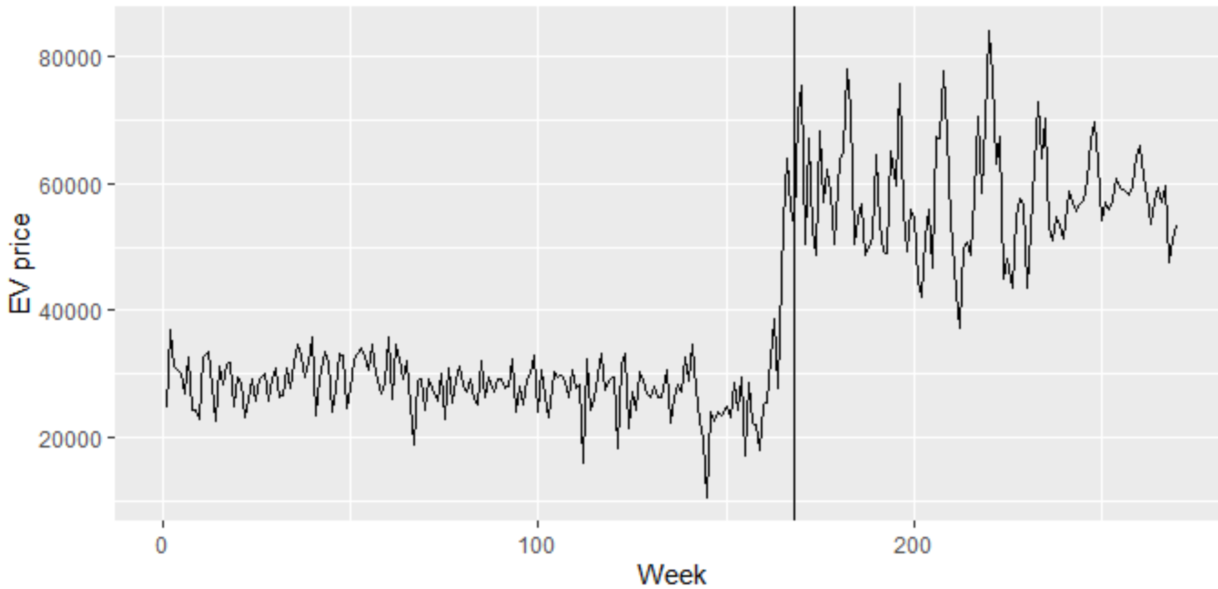

Figure 13 Average EV price over time. The black vertical line represents the cut point.

Nevertheless, all the above results/plots suggest that the tax credit policy itself had a positive effect on the EV market.

7 DISCUSSION & CONCLUSION

This study has some limitations. As I mentioned before, I omit all the hybrid vehicles because from my dataset, I cannot differentiate with a conventional hybrid and plug-in hybrid from the data.

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 of my 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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APPENDIX A

Different Cut-Point

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.

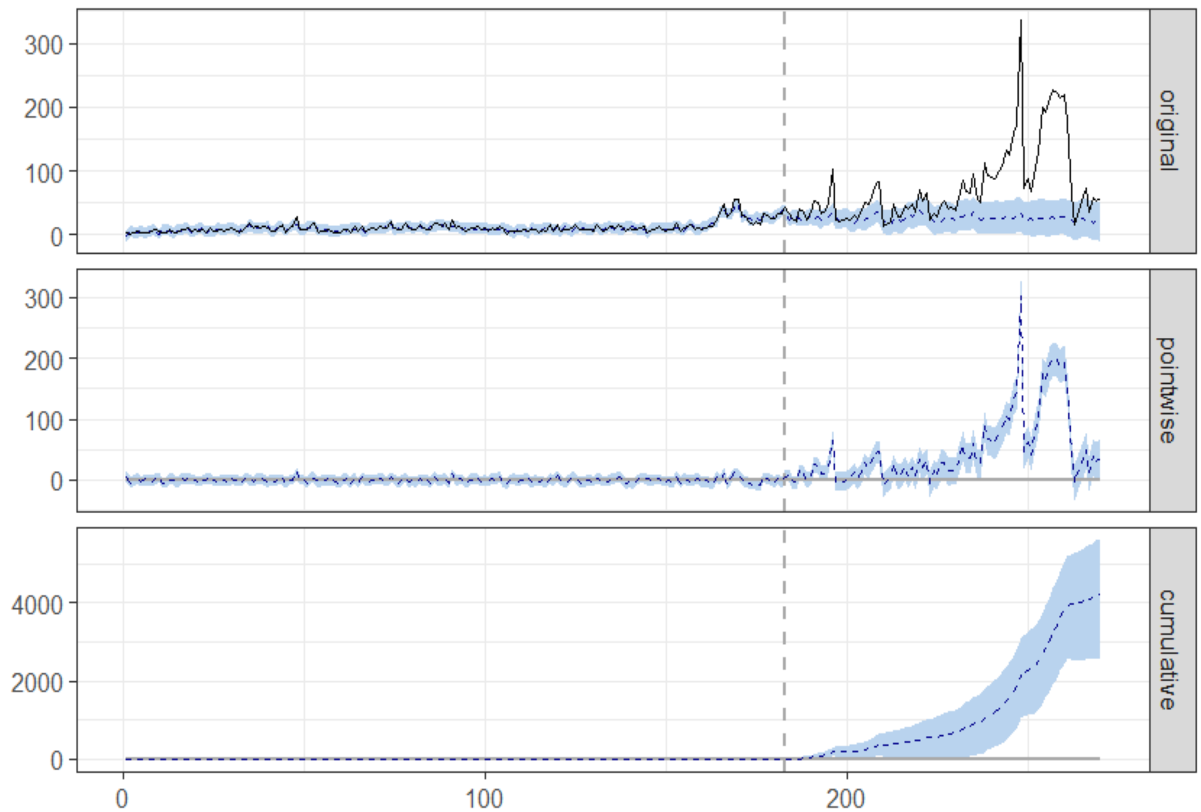

Figure A1 Causal Impact of the tax credit with cut point 1st July 2017

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	4013	2169	5622	856.6
		Relative Effect	*Relative Lower*	*Relative Upper*	*SD*
Relative		164%	89%	230%	35%

Posterior tail area probability, 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-2ln(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 (Akaike, 1974).

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.