Factors Affecting Sales of Electric Vehicles:

A California Case Study

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October 7, 2022

Abstract

Global warming has never attracted as much attention as it does today. Along with other complicated circumstances such as gas price surging, several governments have initiated plans to promote vehicle electrification. Therefore, it is worth researching which issues most support the marketization of electric vehicles (EVs). This paper took government subsidies, oil prices, electricity rates, the number of charging stations, and fuel car prices as variables to measure what factors contribute most to the sales of EVs. We collected county and state-level data on the number of charging stations, electricity rate, the U.S. gas prices, the U.S. consumer price index (CPI) for new cars, and the registration data for EVs in California from several government websites. We chose Sacramento County and San Joaquin County as the test group and control group, where Sacramento County launched an EV-promoting program in 2017, but San Joaquin County did not. We applied the difference-in-difference model and the fixed effect regression model to the data and highlighted the following findings: 1) governments' subsidies are one of the most significant factors that affect consumers' choice of EVs. 2) there is strong evidence of a positive effect of the number of charging stations on the sales of EVs. We hope the above information could help policymakers in the related fields make wiser decisions towards further marketization of EVs.

1 Introduction

As oil prices surge amid the Russia-Ukraine crisis, electric vehicles (EVs) have become more cost-effective for consumers. Together with the increasing awareness of environmental protection, stronger warning signs of global warming, and the rising energy crisis, the International Energy Agency (IEA) and the Clean Energy Ministerial (CEM) have initiated a multi-government policy forum—the Electric Vehicles Initiative (EVI)—with sixteen countries to speed up the introduction and adoption of electric vehicles since 2010 (Electric Vehicles Initiative, 2019). The number of EVs has almost tripled from 2016 to 2020 in the U.S. alone (Desilver, 2021), with 1.8 million registered today. However, the U.S. is not the largest market in the world. EV increased from 1.2 million in 2016 to 11.3 million in 2021 worldwide (Carlier, 2022); Europe and China are the top market players, with 10% and 5.7% market share respectively, while the U.S. counts for 2.0% in 2020 (Desilver, 2021). The fastest growth in EV sales of 60% from 2016 to 2020 also occurred in Europe, compared with increases of 36% in China and 17% in the U.S (Desilver, 2021).

The governments in Asia, Europe, and the U.S. have all enacted various incentives to accelerate EV sales yet gained different outcomes. What factors lead to this drastic difference in EV sales? Which factor is the most effective one regarding EV sales promotion? Do government subsidies or incentives support EV sales? If it does, to what extent does it support? In this paper, we took the following for analysis: government subsidies, gas price, electricity rate, number of charging stations, and price of traditional fuel cars. Since California has the highest EV share among all U.S. states, we chose two counties in California—Sacramento and San Joaquin, where the former had a government incentive in 2017 and the latter without—for comparison, and to analyze the importance of government's subsidy along with other factors. We hope this paper can help policymakers gain a better and more comprehensive understanding of how the factors affect the demand for EV sales and make wiser decisions.

2 Literature Review

2.1 The positive environmental effect of EV

While many people are questioning whether, or to what extent driving an EV is environmentally beneficial since a large portion of electricity still comes from coal burning, sound studies do show EVs contribute less negative environmental effects than traditional gasoline vehicles. In "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors", Holland et al. (2016) argued that the environmental benefit of driving an EV depends on the region, varying from \$0.01 for a metropolitan area to \$0.017 outside of a metropolitan area. While not all benefits can be considered unconditionally—for example, the benefit of driving an EV in California might be overwhelmed by the negative impact of burning coal in other states to generate electricity—undeniably, the development and promotion of driving EV does lead to a positive environmental effect in terms of a national-level scale. Choma et al. (2020) further strengthened the positive environmental effect of EVs by conducting an assessment of the health impact of air pollution in the U.S. They calculated the mortality impact per mile of traditional vehicles attributed to toxic compounds emitted from the tailpipe and compared the result with the changes in greenhouse-gas emissions associated with vehicle electrification. The outcome strongly supports the idea that EVs are greatly beneficial for human health even if they are exclusively powered by fossil fuel plants: the health benefits in 53 metropolitan areas primarily come from the reduction of mortality rate attributed to PM2.5—the main culprit of people's lung disease. Choma et al. (2020) pointed out that in the short term, EV is very likely to be a great opportunity for governments and policymakers to "achieve large public health benefits in the United States."

2.2 Barriers and potential incentives to the process of vehicle electrification

2.1.1 Limited charging infrastructures

One of the most critical troubles EV owners worry about is "range anxiety" (Melliger, van Vliet and Liimatainen, 2018). Unlike traditional fuel vehicles, EVs have fewer charging stations at the initial stage, meaning it is harder for drivers to "refuel" and extend the vehicle's range. Additionally, compared to traditional fuel vehicles that take about only five minutes at gas stations before resuming the journey, EVs take longer to charge. An EV would be stuck in the middle of the road if it runs out of battery, and the driver cannot simply take the battery out and replace a new one. The insufficiency and range stress together hindered consumers from purchasing EVs, thus hindering vehicle electrification.

Moreover, the high investment cost and low rate of profitability of constructing charging stations further exacerbate the problem. According to Huang and

Kockelman (2020), the cost of investing in EV charging stations includes land acquisition, installation, operation, and maintenance. Furthermore, the payback time might be very long. Due to the lower electricity prices for charging at home or the workplace, only 1.5% of EV owners use public charging stations (Madina et al., 2015), primarily when they run out of battery and urgently need to extend their driving range. Therefore, it may take more than five years for a charging station to reach the break-even point, providing the charging rate is at least $6 for a 30-min charge (Huang and Kockelman, 2020). High investment costs and low rates of return burden enterprises and individuals from investing in charging stations, resulting in limited charging infrastructure on the market, further discouraging consumers from purchasing EVs. The consequence of this positive feedback leads to a “Chicken-Eggs dilemma”, stated Shi et al. (2021) in a paper published in 2021.

2.1.2 Potential incentives

There are other factors that barrier the promotion of EVs, but from the point of view of policymakers, they could also be incentives. Gas price is one of the most sensitive factors affecting consumers’ purchasing choices. EV sales in 2006 would have been 37% lower if gasoline prices were staying at the 1999 levels, stated Beresteanu and Li (2011) in a 2011 study. This indicates a strong negative relationship between gas prices and EV demand, meaning policymakers could consider subsidizing EV owners to offset the rise in gas prices. Another important aspect is subsidy or tax credit. A 2015 report (Clinton et al., 2015) pointed out that tax credits have a positive and statistically significant impact on EV adoption, promoting registrations of 700 to 3,500 EVs nationwide since 2011, in which the estimated annual abatement was equivalent to 500 to 2,700 tons of carbon dioxide. The author concluded that a $1,000 increase in tax credit would result in a 2% to 10% growth in per-capita EV registration.

3 Data

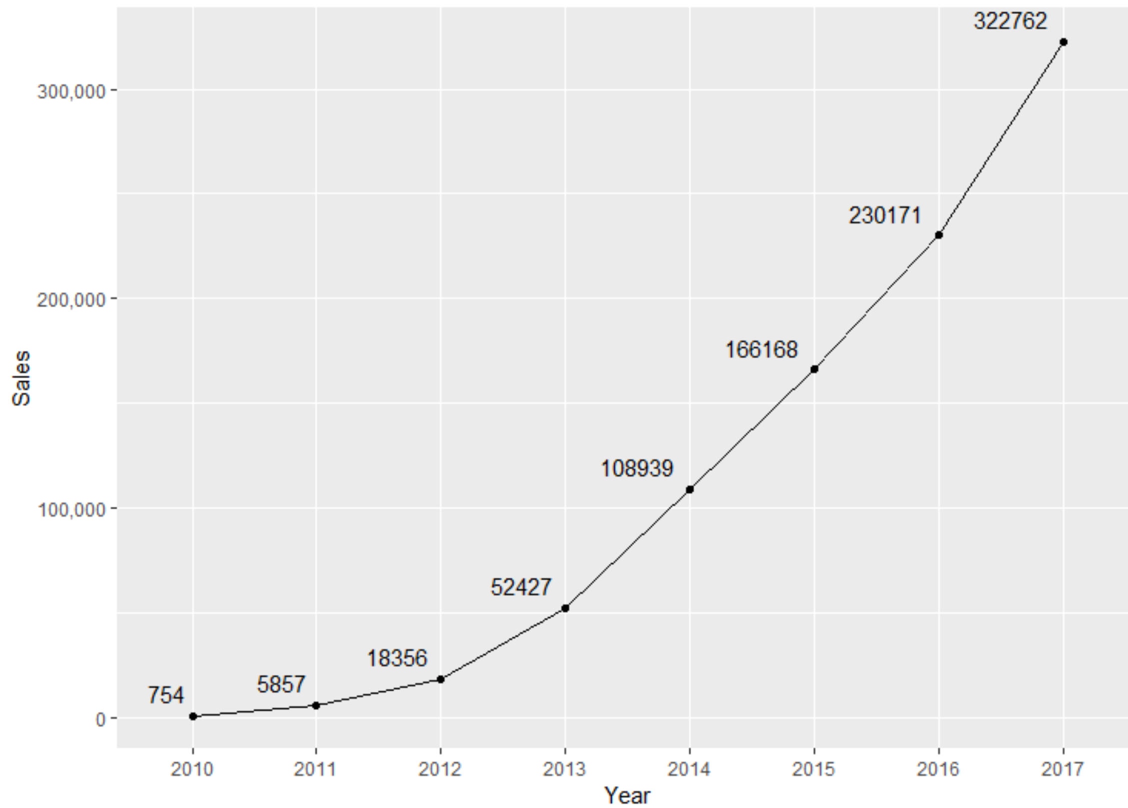
We collected data from several independent sources. This study used several categories of data regarding each factor that might affect EV sales: historical county-level EV charging station numbers in CA from 2010 to 2020 obtained from the U.S. Department of Energy, state-level historical electricity rate, and U.S. oil price from 2010 to 2020 obtained from U.S. Bureau of Labor Statistics, annual U.S. consumer price index(CPI) for new cars and trucks obtained from Bureau of Labor Statistics, and the registration data obtained from Atlas EV Hub (Atlas EV Hub, 2020). As no state-level annual CPI for new cars and trucks are available, we assumed that the California car price change is following the U.S. CPI for new car and trucks trend. In addition, the share of electric vehicle models in recent vehicle sales was about 2.4 % in 2020. Therefore, we assume that EV only takes a very small portion of the sample of CPI for new cars and trucks. We use CPI for new cars and trucks as a price index for gasoline cars (as a substitute for EV). Figure 1 shows that EV sales in CA boomed from 2010 to 2017. There were only 754 EVs registered in California in 2010, but the sales grew exponentially in the following years. Besides, our data shows that oil prices, the number of government's subsidies toward purchasing EVs, the number of charging stations, and the price of fuel cars also have increasing trends in these years.

This paper tries to find the proportional change in EV sales under the influence of different factors. We applied natural log transformation to our raw values to reach this goal. After transformation, Table 1 below provides descriptive statistics of this data.

Table 1: Descriptive Statistic

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(sales)	440	4.879	2.757	0	11.338
ln(oil_price)	440	4.192	.365	3.607	4.564
ln(electricity_rate)	440	2.687	.077	2.566	2.89
ln(station)	440	4.238	1.838	0	8.17
ln(other_cars)	440	4.978	.035	4.928	5.031

Figure 1: EV sales in CA from 2010 to 2017



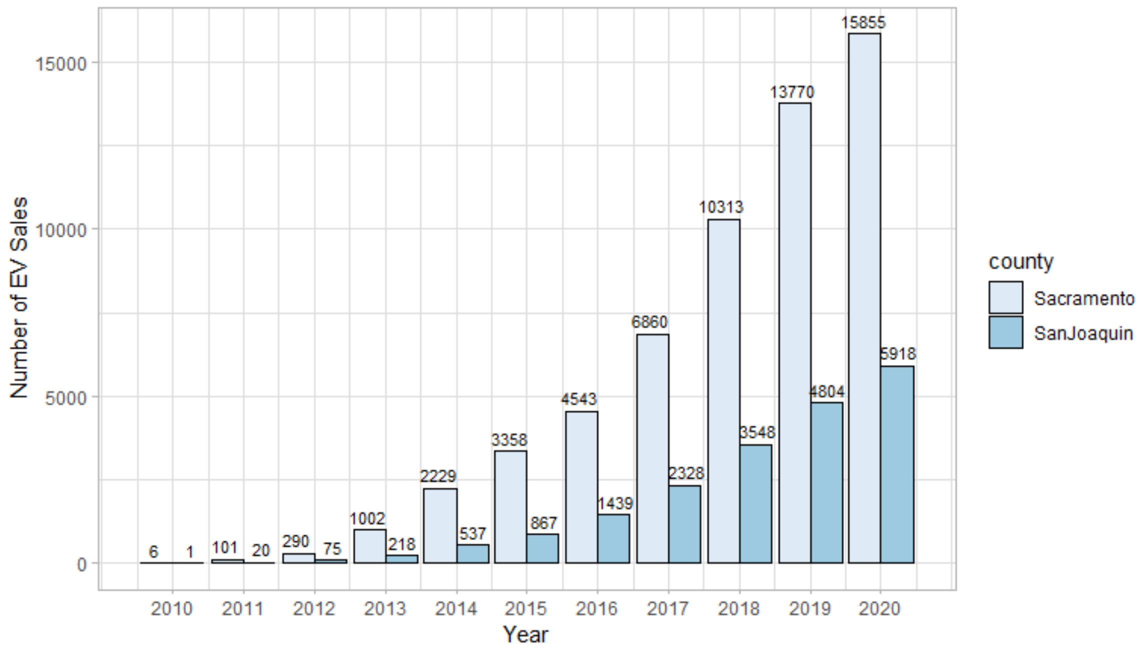
Note. The data is generated from [“State EV Registration Data”], by Atlas EV Hub (https://www.atlasevhub.com/materials/state-ev-registration-data/).

4 Methodology

4.1 Difference in Difference

We started by measuring the causal effect of subsidies by implementing the Difference in Difference estimation. We picked two counties, Sacramento County (test group) and San Joaquin County (control group) in California. Sacramento County launched a comprehensive program to promote the growth of EV In 2017 (County of Sacramento et al., 2017) where San Joaquin County did not enact any related program that year. In this program, Sacramento Metropolitan Air Quality Management District initiated an incentive program called Clean Cars 4 All (CC4A) that offered financial incentives to income-qualified residents in disadvantaged communities. Participants could receive up to $9,500 to purchase an eligible new or used clean vehicle (www.airquality.org, n.d.). Figure 2 below displays the historical sales of EVs in these two counties.

Figure 2: EV Sales in Sacramento and San Joaquin



Note. The data is generated from ["State EV Registration Data"], by Atlas EV Hub (https://www.atlasevhub.com/materials/state-ev-registration-data/).

An important prerequisite assumption that needs to be satisfied for the validity of the DiD model is the parallel trends assumption. To this end, this paper generates dummy variables for the experimental group and time for the three periods before the policy occurs. We set the current year as 2018, the following year the policy was launched, and denoted it as the variable "*current*" in this table. Then we generated three dummy variables: *pre_3*, *pre_2*, and *pre_1*, representing three years before 2018, which are 2015, 2016, and 2017. Finally, we ran a linear regression analysis on these variables to get the result. This result shows that none of the dummy variables *pre_3*, *pre_2*, and *pre_1* representing the period before the policy occurs are significant, indicating the changes in the dependent variable between the experimental and control groups before the policy occurs satisfy the parallel trend. And the dummy variables representing the post-policy occurrence current were all positively correlated with ln(sale) at least at the 1% significance level, indicating a significant policy effect. Table 2 below illustrates the parallel trends test in detail.

As the parallel trends assumption is satisfied, we are confident about the validity of the Difference in Difference estimation of policy effectiveness. In the following discussion, *DiD* represents for government's subsidies.

Table 2: Parallel Trends Test

VARIABLES	(1) ln(sales)
pre_3	0.308
	(0.38)
pre_2	0.349
	(0.38)
pre_1	0.426
	(0.38)
current	1.667***
	(0.39)
Constant	4.857***
	(0.02)
Observations	439
R-squared	0.974
control variable	YES
county	YES
year	YES
F	4.661

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note. The variable *pre_3* denotes year 2015. The variable *pre_2* denotes year 2016. The variable *pre_1* denotes year 2017. The variable *constant* denotes year 2018.

4.2 The fixed effect regression model

We assume that EV sales positively correlate with the electricity rate, the number of charging stations, and subsidies. On the other hand, oil prices and the price of other cars would be negatively correlated with EV sales. We run Pearson correlation analysis to measure the strength of linear associations between two variables. Table 3 below shows the result.

Table 3: Pearson Correlation Analysis

	ln(sales)	did	ln(oil_price)	ln(elecrity_rate)	ln(station)	ln(other_cars)
ln(sales)	1					
DiD	0.089*	1				
ln(oil_price)	-0.326***	-0.0140	1			
ln(electricity_rate)	0.491***	0.106**	-0.674***	1		
ln(station)	0.729***	0.0420	0.0660	-0.0770	1	
ln(other_cars)	-0.355***	-0.0690	0.852***	-0.760***	0.0370	1

The results showed that the core explanatory variables *DiD* have a significant positive relationship with *ln(sales)*, which is consistent with the expected hypothesis, and the other explanatory variables such as *ln(oil_price)* and *ln(station)* were significantly correlated with *ln(sales)* at least at 1% significance level. However, considering that the correlation matrix only measures the relationship between bivariate variables and does not exclude the interference of control variables and hidden variables (such as time effect and individual effect), the results are for reference only, and we need further regression analysis to determine the specific relationship. In addition, the absolute magnitude of the correlation coefficient between the explanatory variables is smaller than 0.9, thus we can also preliminarily exclude the possibility of collinearity of variables.

A multicollinearity test is required to further check whether the collinearity of variables exists in the data. The presence of multicollinearity is generally detected by the variance inflation factor (VIF): The ratio of the variance when there is multicollinearity between the explanatory variables to the variance when there is no multicollinearity. The greater the VIF, the more serious the covariance. The empirical judgment method shows that when 0<VIF<10, there is no multicollinearity; when 10≤VIF<100, there is strong multicollinearity; when VIF≥100, there is severe multicollinearity. Table 4 below shows the results of the multicollinearity test of the model. The VIF values of all variables are less than 10, thus the indicators selected in this paper do not have multicollinearity.

Table 4: Variance Inflation Factor

	VIF	1/VIF
ln(other_cars)	4.777	.209
ln(oil_price)	3.718	.269
ln(electricity_rate)	2.412	.415
DiD	1.023	.978
ln(station)	1.013	.987
Mean VIF	2.589	.

Since no multicollinearity exists between variables, we can decide which model should be selected in the next step. For panel data, the most important thing is determining the model suitable for analysis. Panel data may be mixed effect model, fixed effect model, and random effect model. Hausman test can be applied to determine the choice of random effect model or fixed effect model, F test in fixed effect model can determine the choice of fixed effect model or mixed effect model. This paper mainly uses the Hausman and F tests to determine what model is suitable for the analysis of the data in this paper. The test results are shown below.

Table 5: Hausman (1978) specification test

	Coef.
Chi-square test value	22.356
P-value	0

Figure 3: F-test

F test that all u_i=0: F(57, 378) = 47.99	Prob > F = 0.0000

The Hausman test result statistic was 22.356, with p=0.00<0.05, indicating that the original hypothesis was rejected, and a fixed effects model should be chosen. This paper also conducted an F-test, and the F-test statistic was 47.99, with p=0.00<0.05, so the original hypothesis was rejected, and the fixed-effects model was chosen.

Thus, by combining the results of the previous Hausman test and the F-test, we exclude the endogeneity problems brought by individual effects and time effects. This paper finally adopts the fixed-effects model for regression analysis as follows:

$$\begin{aligned} ln(Sales)_{i,t} = \alpha + \mu_i + \lambda_t + \theta treat_i \times post_t + \beta_1 ln(oil\_price)_{i,t} + \beta_2 ln(electricity\_rate)_{i,t} + \\ \beta_3 ln(station)_{i,t} + \beta_4 ln(other\_cars)_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

In this model, α denotes constant. μ_i denotes individual fixed effect. λ denotes time fixed effect. βs are coefficients. $ln(oil\_price)_{i,t}$, $ln(electricity\_rate)_{i,t}$, $ln(station)_{i,t}$, and $ln(other\_cars)_{i,t}$ are variables.

Stepwise regression is used to verify the hypotheses by enhancing the reliability of the results. Table 6 illustrates the stepwise regression. We achieve the stepwise regression by forward selection. Begins with only the *DiD* variable in the model, tests each variable as it is added to the model, repeating this process until the results are optimal. In this table, regression (5) is the optimal result. In this regression, the core explanatory variable *DiD* has a significant positive relationship with the dependent variable ln(sales) at 1% significance level with a coefficient of 1.531, which implies that the policy effect of subsiding purchasing EV increased EV sales by 153.1% on average. The second explanatory variable *ln(oil_price)* also has a positive relationship with the dependent variable *ln(sales)* at 1% significant level with a coefficient of 2.587. This shows that a 1% increase in oil price would lead to a 258.7% increase in EV sales. The third explanatory variable *ln(electricity_price)* has a positive relationship with the dependent variable *ln(sales)* at 1% significant level with a coefficient of 17.460, implying that an increase in the electricity rate for 1% increases sales by 1746% on average. This result is actually contrary to our assumption that electricity rate and EV sales are negatively related. However, despite EV prices rising in the past few years, it is still a cheaper choice than gasoline. This result is acceptable for our research. According to AAA (gasprices.aaa.com, 2022), the average price of normal gasoline in the United States as of June 1 was $4.67, and prices had increased 41% since the beginning of this year. In contrast, the price of electricity has been comparatively consistent and low compared to the cost of gasoline and diesel. On average, residential power costs 13 cents per kilowatt hour in the United States (U.S. Energy Information Administration, 2016). Until now, the electricity rate is still not essential for consumers when considering an EV. The fourth explanatory variable *ln(station)* has a significant positive relationship with the dependent variable *ln(sales)* at 1% significant level with a coefficient of 1.219, implying that a 1% increase in the number of charging station leads to a 121.9% increase in sales. The last explanatory variable *ln(other_cars)* has a negative relationship with the dependent variable *ln(sales),* indicating that as the price of fuel cars decreases by 1%, the sales of EV increase by 1182% on average.

Besides, the F-values of the regression also indicate that the overall coefficient of the model regression is significant. The R-squared of the equation is also above 0.9; the model fits well and has strong explanatory power.

To ensure the validity of the result, we also test the heterogeneity between two observations, Sacramento County and San Joaquin County, by running a regression in these two observations. Table 7 illustrates the result.

In this table, we can see that the coefficients in these two regressions are very close and with a 1% significant level, which implies that our model successfully applies to both counties.

Table 6: Stepwise FE Regression

VARIABLES	(1) ln(sales)	(2) ln(sales)	(3) ln(sales)	(4) ln(sales)	(5) ln(sales)
DiD	1.531***	1.531***	1.531***	1.531***	1.531***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
ln(oil_price)		-31.439***	-8.569***	-8.494***	2.587***
		(0.07)	(0.02)	(0.02)	(0.25)
ln(electricity_rate)			13.971***	14.017***	17.460***
			(0.03)	(0.03)	(0.07)
ln(station)				1.219***	1.219***
				(0.03)	(0.03)
ln(other_cars)					-11.820***
					(0.25)
Constant	-1.587	140.211***	3.832***	1.189***	1.189***
	(0.98)	(0.32)	(0.08)	(0.10)	(0.10)
Observations	440	440	440	440	440
R-squared	0.913	0.974	0.974	0.974	0.974
Number of groups	58	58	58	58	58
county	YES	YES	YES	YES	YES
year	YES	YES	YES	YES	YES
F	4244	9120	9120	880.1	880.1

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Heterogeneity Analysis

VARIABLES	Sacramento lnsales	San Joaquin lnsales
did	1.559***	1.505***
	(0.07)	(0.16)
lnoil_price	2.572***	2.577***
	(0.25)	(0.25)
lnelectricity_rate	17.399***	17.428***
	(0.07)	(0.07)
lnstation	1.218***	1.219***
	(0.03)	(0.03)
lnother_cars	-11.773***	-11.795***
	(0.25)	(0.25)
Constant	1.187***	1.188***
	(0.10)	(0.10)
Observations	431	431
R-squared	0.974	0.974
Number of groups	57	57
county	YES	YES
year	YES	YES
F	89.37	90.09

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5 Conclusion

This paper examines how government subsidies, oil prices, electricity rate, number of charging stations, and fuel car prices contribute to EV sales. The Difference in Difference estimation analysis on data in California shows a positive effect on the government's subsidies. From the result of this estimation, we can conclude the government's subsidies are one of the most significant factors that affect consumers' choice of EVs. The government could introduce more incentives and laws, such as tax reductions and direct purchasing subsidies, to stimulate consumers to purchase EVs.

The fixed effect regression analysis provides evidence of the positive effect of the number of charging stations. Charging networks can boost EV sales by providing convenience to consumers. The government could also subsidize the construction of charging stations. The increasing number of charging stations is another important factor affecting consumers' choice of EVs. Currently, the number of charging stations is still far less than gas stations, and the distribution of charging stations is also uneven. Finding a charging station could be a pain for consumers who live in suburban and urban areas, preventing them from choosing EVs. EV manufacturers could also contribute to constructing charging stations.

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