The Impact of Subsidy on EV Adoption: Evidence from China

Xinyuan Yang,Chengxin Qian

Abstract

Recent decades have witnessed a rising demand and production of electric vehicles as green energy substitutes to regular automobiles. It is of great interest to government policy makers to decide which industrial policy should be implemented to boost the development of this fresh industry. In this project, we collect city–month level data of EV sales and subsidy for 15 cities in China from 2016 to 2019. Utilizing panel regression with IVs, we demonstrate that a 10,000 Yuan ($1,600) increase in purchase subsidy would boost regional EV sales by around 6% to 11%. Various regression setups corroborate the robustness of our estimation.

1 Background Introduction

Electrical vehicle (EV) has been a hot issue in the era of global warming. Around the globe roughly 30% of the greenhouse gas emissions come from on-road vehicles. China started the policies for boosting EV sales in 2009 for the purpose of energy security, but despite generous fiscal subsidies, up until 2012, there are only a little over 10,000 EV sold annually. This number gradually increased starting in 2013, reaching 400,000 in 2015. In 2011, EV sales in China accounts for 10.4% EV sales globally; whereas in 2019, the ratio grew to over 50%.

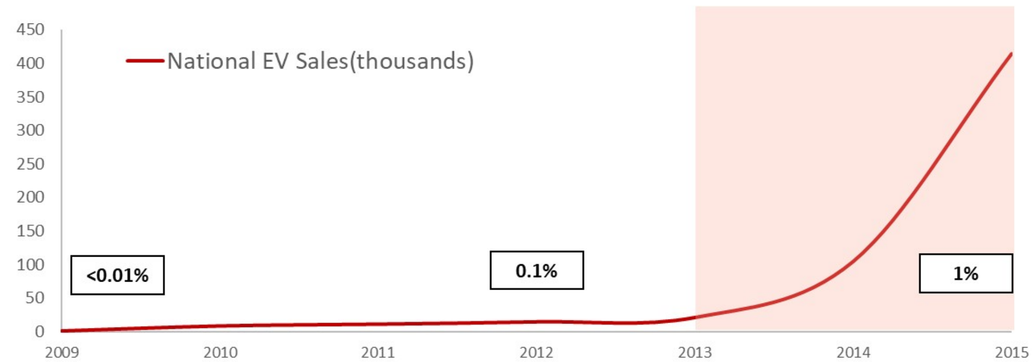

Figure 1: National EV Sales (2009 to 2015)

The dramatic increase of EV sales are due to several reasons. Firstly, according to the survey conducted in (Helveston et al., 2015), approximately two-thirds of Chinese car buyers are first-time buyers of cars in general, the increase of EV sales in China could be due to the general increase in car adoption as people get richer. Secondly, there are multiple policies designed to induce the adoption of electric cars. These include fiscal and tax incentives, preferential treatment to EV when it comes to traffic regulations, and electricity bill allowance. From the year 2009 to 2016, the central government has spent over $12 billions alone on national subsidies.

Since EV is a new type of durable goods to consumers, it is particularly of interest to the government decision-makers to see what industrial policies would most efficiently drive up EV sales. In this paper, we exploit the variation in the city-level EV purchase subsidies and traffic controls in China and attempt to draw an inference on the effectiveness of various popular policy tool. Our study would provide insight to government on future policy design.

1.1 Types of Policies

The national policy on EV started in 2006 with a long-term science and technology development plan, during which period the focus was on R&D and the new energy vehicle (the term NEV was used in the Chinese policy documents) became a priority theme. Over the years from 2009 to 2012, the state EV demonstration project introduced nearly 20,000 NEVs in 20 demonstration cities, and subsidy 1.0 was issued. From the year 2013 to 2015, the second-stage demonstration project was carried out during which the demonstration expanded to 38 cities. These cities adopted new wave of subsidies and for the first time, subsidy phase-out plan was developed.

Before 2012, the policy system was mainly supported by subsidy and was unsystematic. From 2013, the policy system has been made more comprehensive. The policies on charging infrastructures were aggregated in the year 2014-2015. Other policies implemented on the demand side were listed below:

1. **Fiscal subsidies:** both at the central and local levels (2009 to 2019), at most ￥ 60,000 at both national and local level. The policy were published nearly every year. The vehicles that meet the requirement on the technical details listed on the policy document can apply to be eligible for the subsidies and be listed on the "Catalogue of recommended models of energy-saving and new energy vehicle demonstration and application projects (herein referred to as 'Catalogue')". It is important to note that only vehicles listed on the 'Catalogue' are eligible for subsidies, and the 'Catalogue' updated every several times a month.

2. **Tax exemptions:**

   (i) **Purchase tax exemptions.**
   Office of the State Council declared in July 2014 that the NEVs meeting the specified technological standards are eligible for exemption from purchasing tax. The effective date of the policy are from 2014-09-01 to 2017-12-31. This policy was renewed again on 2017-12-26 to extend to 2020-12-31, and further extend to 2022-12-31 on 2020-04-16. The purchase tax was considerable 10% of the price of vehicle.

   (ii) **Travel tax exemptions.**
   The travel tax was first exempted in 2012 and then renewed in 2015. But since it is only couple hundreds a year, it is not very much influential to consumers' decision in EV purchases.

3. **Purchasing restrictions:** 6 major cities have implemented restrictions to curtail new vehicle registration: license lottery (Beijing) and license plate auction system (Shanghai). In 2015 the auction success rate is 4.3% and the average price of a license plate reaching ￥ 80,000.

   - **Shanghai**: licence plate auction system started in 1994
   - **Beijing**: vehicle quota system with licence lottery in January 2011
   - **Guangzhou**: starting in June 2012, half lottery, half auction system
   - **Tianjin**: starting in December 2013
   - **Hangzhou**: starting in March 2014
   - **Shenzhen**: starting in December 2014

4. **Traffic restrictions:** limited road access based on licensing plate. For example, when a date is an odd number, motor vehicles with an even-numbered license plate are restricted, and when the date is an even number, motor vehicles with an odd-numbered license plate are restricted. These policies are implemented at local levels by policy bureaus, and mostly prior to the year 2016. However, the influence of traffic restrictions on consumers' decision in purchasing EV was unclear. In November 2011, central government requires all regions to give preferential treatment in terms of purchasing and traffic restrictions to all electric vehicles. However, rich anecdotal evidence suggests that some families would rather purchase a second gasoline vehicle than EV to bypass the traffic restrictions.

Given the complexity and experimental characteristics of the EV policies in China, we will restrain our focus to only subsidies (both at the national and local level), tax exemptions and purchase restrictions. Hence the timeline of our focus will be ranging from January 2016 to October 2019, during which period the policies are relative focused on the demand side (inducing consumer to purchase EV) and stable.

1.2 Central Government Policies

The detailed list of national subsidies and tax exemptions from the year 2016 to 2019 are listed in figure 9 in the **Appendix**. The subsidies requirements are different for electric vehicles for different purposes (generally there are three categories: passenger vehicles, public transit vehicles, and special purpose vehicles). We are only interested in passenger vehicles as the purchase of these passenger cars are more market-based and the sales data obtained only include passenger vehicles.

The subsidies for passenger EVs are divided into three categories: **PHEV** - plug-in hybrid electric vehicle (for above 50km range cars), **BEV** - battery electric vehicle (subsidies differ by range) and **FCEV** - fuel cell electric vehicles. We only included battery electric vehicle for the analysis as it accounts to the majority of EV sales in China and has enjoyed the majority of subsidies (see column 'Policies' in figure 9).

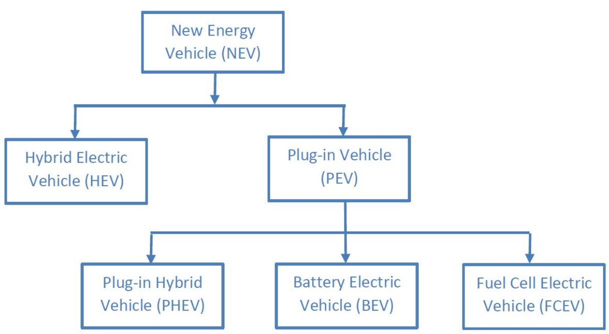

Figure 2: EV Categories

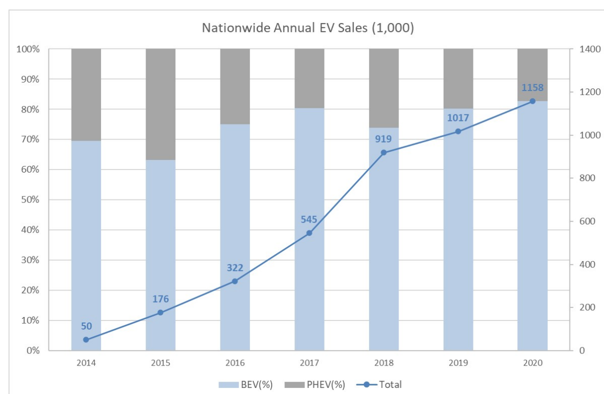

Figure 3: EV Sales % (Blue: BEV, Grey: PHEV)

Because we are interested in the variations in subsidies on the consumer demand for electric vehicles, we constructed a continuous variable of national subsidy data using policy documents published by the Chinese central government. The subsidy value is based on the maximum subsidy given to the battery electric vehicles (herein referred to as BEV). Although technical standards changed twice (from year 2017 to 2018, and then again in 2019), as shown in figure 4, we took the maximum national consumer subsidies for passenger EVs as our continuous variable for national subsidy.

Range Powered by Electricity (test cycle/km)						
Category	BEV			PHEV		
Range	100<R<150	150<R<250	R>250	R>50		
2016	2.5	4.5	5.5	3		
2017	2	3.6	4.4	2.4		
	BEV					PHEV
	150<R<200	200<R<250	250<R<300	300<R<400	R>400	R>=50
2018	1.5	2.4	3.4	4.5	5	2.2
			250<=R<400		R>=400	R>=50
2019	--	--	1.8		2.5	1

Figure 4: National-Level Subsidies (2016-2019) for Passenger EVs

There are few things to note on the national consumer subsidies. First, from year 2016 to 2019, the subsidy policy documents are published on average every year. The document **Caijian [2015] No.134** was supposed to set the subsidy guidelines for year 2016 to 2018, the level of subsidies were adjusted thereafter for both 2017 and 2018 (as shown in **Caijian [2016] No.958** and **Caijian [2017] No.172**). This reflected the central government's repeated policy formulation during this experimental period for subsidy phase-out, because nobody at that stage knew how consumers would react to a decrease in purchase subsidies. Seeing that decreasing the subsidies did not drastically reduce the purchase of EVs, more stringent technical details were put out for the year 2018 and then in 2019 (as seen in 4). Therefore, the national subsidy is inherently endogenous, its policy-making process is highly responsive to the market demand for EVs.

Second, due to the fact of the frequent modification of subsidy policies, there are periods of uncertainties. The policy document providing subsidy outlines are not always published on time. For example, in the document referenced as (Caijian [2018] No.18) in figure 9, the maximum subsidy was adjusted from 44,000 RMB to 50,000 RMB, but the document was published in mid-February, 2018. The month January is a month of uncertainty for both EV wholesalers and consumers, we hence use the same subsidy as in December 2017 for January 2018. However, the uncertainty concern is greater on the local level.

The third key-point to note is that national subsidy level determines the local levels. A great number of cities make local subsidy level as a percentage of the national subsidy level. The central government also set guidelines for the local subsidies, first the total local subsidies on all tiers (provincial and prefectural) are capped at 50% of the central level **(Caijian [2016] No.958)**, then the central government requires the local government to no longer provide subsidies for EVs **(Caijian [2019] No.138)**.

Figure 5 shows the relationship between national subsidies and the EV demand for all 15 cities (red color indicates the cities with a purchase restrictions). First it is obvious to note that consumers respond to subsidies by anticipating the decrease in future subsidies. This usually happened at the last month of the year. For example, when the 2019 subsidies are drastically lower than the previous years, there are more EV purchased on December 2018. In addition, there are spikes of EV demand during the two transitional periods, after which the subsidies are greatly reduced. Second, there is seasonal effects on the EV demand, both due to the end-year bonuses and car promotions. Finally, the six cities with purchase restrictions generally have a higher demand for EV cars. Particularly Beijing, shown as the darkest red in the figure.

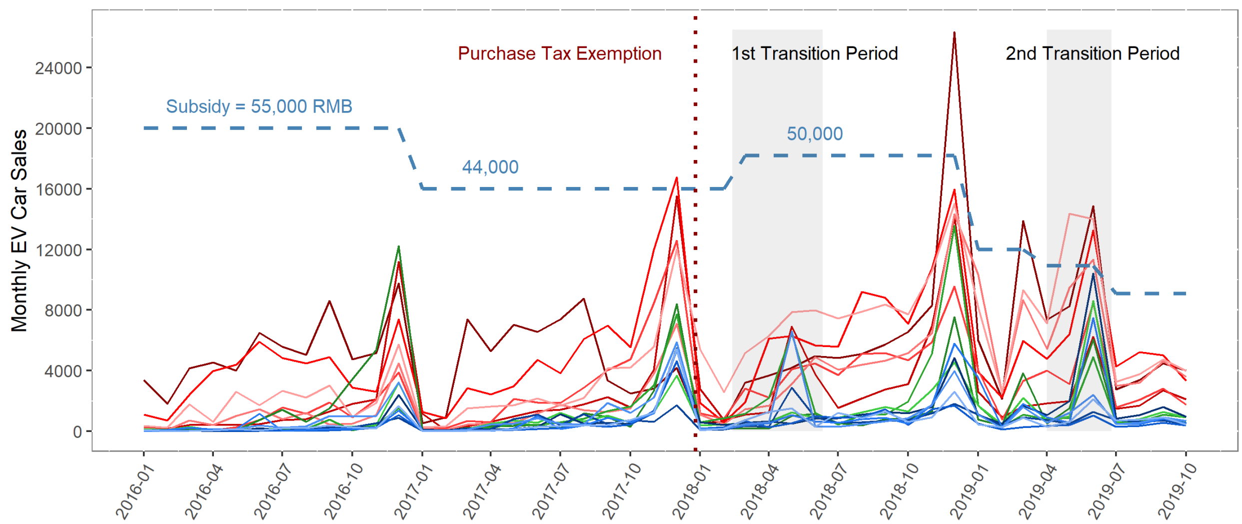

Figure 5: National-level subsidies and EV sales comparison

1.3 Local Policy

The local subsidy policies are closely followed with the national subsidy policy. Local policies are generally implemented at the prefecture level (city), although sometimes both provincial and prefecture financial bureaus share the local fiscal subsidy expenditures. We extract the local subsidy policies the same way we extract from the national subsidy policies.

It is important to note that, the local subsidies would have very different impact on the EV adoption given other relevant EV policies. For example, Hangzhou and Nanjing, both cities part of the Yangtze River Delta cluster, have very different EV sale numbers (monthly EV sales per 10,000 person as shown in fiture 6) despite the similarities in their social-economic status in table 4. As outlined above, both Shanghai and Hangzhou have purchase restriction policies implemented prior to 2016, whereas Nanjing never imposed purchase restrictions. Imposing purchase restrictions on automobile vehicles while giving exceptions to EVs could induce consumers to choose EV over traditional fuel vehicles.

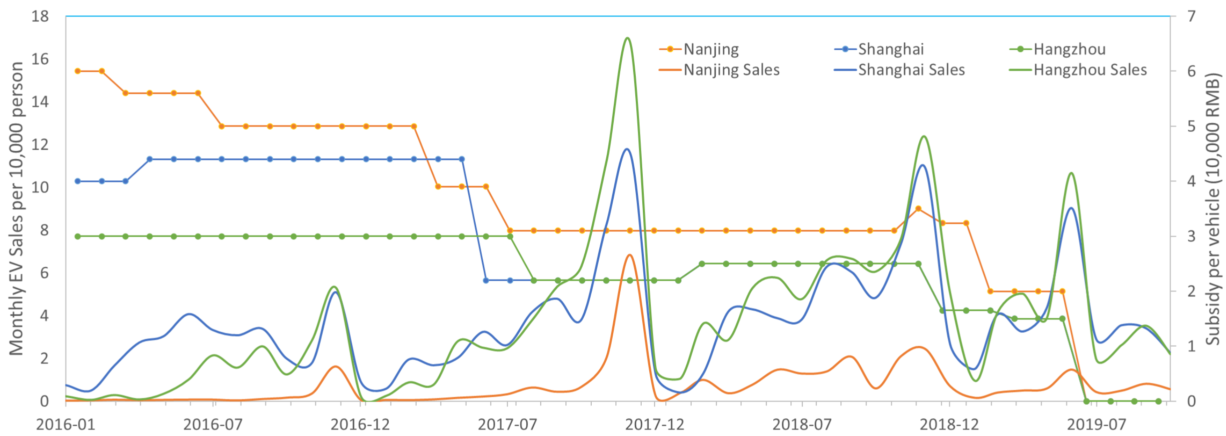

Figure 6: City-level subsidies and EV sales comparison

2 Literature Review

Factors influencing EV adoption rates spans consumer attitude which is mainly analyzed in stated preference analysis, technology factors such as battery costs and performance characteristics, consumer characteristics, and fuel prices (identified by Diamond in a cross-sectional analysis of hybrid registration data from the United States). Along with the traditional factors, state/regional policies for EV market, effects of charging station and seasonal fixed effects are widely researched in this field. Nonetheless, the EV sales within the time range from 2016 to 2019 in China has not been investigated using regression analysis yet. By studying this period when subsidy policy gradually phased out from the market and incorporating necessary factors in our empirical design, this project aims to further determine the magnitude and significance of subsidy policy in China's EV market.

2.1 Review of Financial and Regulatory Incentives

Since China's former President's declaration on developing new energy vehicles in 2009, China has implemented various policies to develop Electric Vehicle market. In Zhang et al. [b], the review divided consumer-side state policies into two categories: finance policy, and infrastructure promotion policy. Finance policy mainly includes price subsidy, reduced vehicle and vessel tax, and exemption from the purchase tax. Infrastructure promotion policy promotes adoption through tax and fee discount, charging pricing, traffic priority, and oil consumers limitation.

Empirical studies about estimating the impacts of incentives are mostly based on sales of hybrid electric vehicles (HEVs) or plug-in hybrid electric vehicles (PHEVs). Li and Beresteanu established both demand and supply models based on hybrid sales data, and found out that federal income tax incentives account for 27% hybrid vehicle sales in 2006. Jenn et al. evaluated the Energy Policy Act of 2005 in the United States using econometric methods and data between 2000 and 2010, and found that the Energy Policy Act had a positive and statistically significant effect on the sales of HEVs. Sales increase by 0.0046% per dollar of incentive, but only when the incentive provided was greater than $1000. From an international perspective, Sierzchula et al. analyzed electric vehicle adoption of 30 countries in 2012 using multiple linear regression analysis and found that financial incentives to be significant and positively correlated to a country's electric vehicle market share.

Nonetheless, economic incentives are not guaranteed to increase adoption (Gneezy et al.). Wang et al. [b] found that the financial incentive policy has no significant effect on intention to adopt EVs using survey data collected from 320 consumers in China.

Aside from traditional financial incentives, due to traffic congestion and related air pollution in China, license plate-control policy is implemented in Beijing, Shanghai, Guangzhou, Shenzhen, Hangzhou, Tianjin and Guiyang. The vehicle quota policy controls vehicle ownership by restricting new license plate registrations except for EVs. In a research of EV sales in 41 pilot cities in China for year 2013 and 2014, Wang et al. [a] found that license fee exemption is one of the four driving factors in EV market using electric vehicle sales data. Zhang et al. [a] found that license plate lottery and subsidy policies are both among the most influential factors in promoting EVs in Beijing using survey approach. Xiao et al. argued that the quota system is less effective compared to a progressive tax system in vehicle control using welfare analysis.

2.2 Charging Station's Network Effects

Many research have identified availability of charging stations as an important factor in EV adoption (Yeh, Struben and Sterman, Egbue and Long, Tran et al.). Empirically, Sierzchula et al. analyzed the effect of charging station in an international level using data of 30 countries in 2012 and results in the paper suggested that charging infrastructure was most strongly correlated to electric vehicle adoption. Mersky et al. also concluded that access to Battery Electric vehicles charging infrastructure, being adjacent to major cities, and regional incomes had the greatest predictive power for the growth of BEV sales in Norway.

3 Research Design

In this paper, we evaluate subsidy's effect on Electric Vehicle adoption in China by leveraging the fact that subsidy provides monetary incentives for consumers to purchase BEV instead of traditional fuel-based vehicles. This naturally gives rise to our dependent variable: EV sales. Considering that our research focuses how subsidy policy helps promote EV adoption in China, intuitively all cities in China are eligible to be unit of analysis. However, due to limited data and time, it is impossible to conduct an analysis of that range, and instead we focus on 15 cities with data availability. We use regression analysis approach to quantitatively evaluate to what extent subsidy affects EV sales in China and whether this effect is statistically significant.

3.1 Empirical Concern

As we choose regression as our research approach, to satisfy initial assumptions and ensure the validity of our results, we first address potential empirical concerns regarding regression analysis.

Endogeneity

The greatest concern is the endogeneity of the subsidy variable. To be specific, since policy-making in China is highly responsive to the market and adaptive, simultaneity would be of highly likely in a sense that an increasing sales of EV would prompt local government to reduce policy intensity or vice versa. In addition, throughout the year of the EV industrial development, China experienced rapid growth, and often the growth are different across regions (e.g. coastal and inland). Hence we should acknowledge the potential biases from time and provincial variant unobservables. In this light, we want to find an instrument for the policy variable.

Potential Instrument

1. A class of candidate IVs is related to the tax revenue of local government. The logic is that, more abundant local budget would offer local policy-makers greater room for subsidy hence IV relevance is established. Due to data availability, we have only province-level tax revenue data, which fails to provide sufficient granularity in analysis and lacks representation of city-level data. Hence, using tax revenue as instrument is not ideal.

2. Total car ownership at city level is a possible instrument for the subsidy variable. Relevance is satisfied as more car ownership means possibly more subsidy provided since it encourages people's purchase. This instrument's exogeneity is questionable as it could be correlated with EV sales through culture or economic development status channel.

3. Another potential instrument is the percentage of subsidy provided by local government as compared to national subsidy. In this case, a greater ratio is accompanied by larger local subsidy, which meets relevance. Figure 7 demonstrates the relevance. And as the local subsidies are provided as a percentage of the central government subsidies, this percentage is more or less arbitrary. However, as outlined in previous sessions, the central government regulated the local subsidies twice during the time period we are interested in, the exogeneity might be of concern as well.

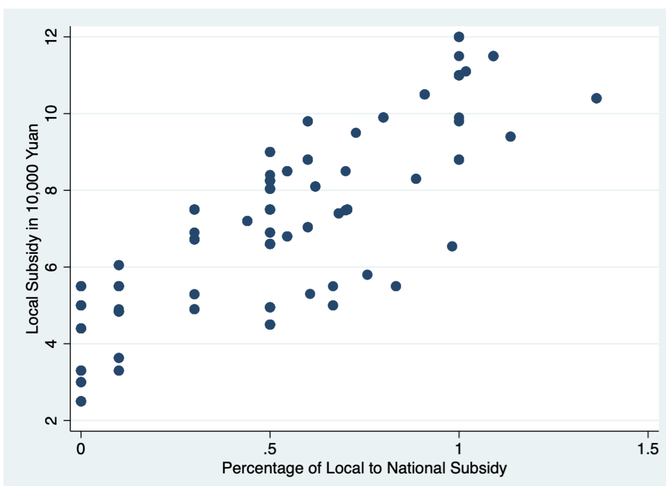

Figure 7: IV Relevance

Heterogeneity and Related Omitted Variable Bias

Another concern is the heterogeneity of the cities in our sample and the related omitted variable bias. For example, the same level of subsidy would probably generate greater intensive for the residents in the regions where EV license is free to apply, but less for the others. Also, the license regulation policy is probably correlated with subsidy in that a higher subsidy is usually implemented together with less restricted license application. To control such city-level difference, we would want to include a set of other policy controls, such as an indicator of the license application restriction. In the panel regression, such influence is captured by the fixed effect.

4 Data

We construct a panel data in city–month unit for around a dozens of representative cities in China that have a EV market. The sample spans from Janurary 2016 to October 2019, during which periods the policies towards electric vehicle in China are relatively "stable". The main response variable is the EV sales per city, and the regressors are those EV-related policies and infrastructures (i.e. charging stations) and classical city-level socio-economic controls. The socio-economic data on cities are obtained from the government statistics bureau, these include annual data on population, quarterly data on provincial GDP, annual averaged salary data for each city, annual total number of cars for each province.

The EV consumer subsidies on both central and local levels are constructed by aggregating dozens of policy documents found in either government websites or archived in industrial associations such as CAAM (China Association of Automobile Manufacturers, as outlined in **Background Introduction** section on policies. The policy data was constructed as a continuous variable on the monthly level. The Y-variable monthly EV sales data for each city is based on the auto-insurance data after purchase.

For data on charging poles, we obtained monthly data in each province for exactly the same time period of our study. It is of importance to note that, during this period there are also central government policies on promoting EV infrastructures so that companies can apply for subsidies based on the number of EV poles constructed. Normally this variable is considered endogenous and would require instrument (for example using the number of supermarkets), however, in our case, we treat it as exogenous. There are ample anecdotal evidence suggesting that the active application rate of charging station is less than 1%. Although there are massive charging station infrastructural implement ion from 2016 to 2019, many of these are simply the result of rent-seeking behaviors to get subsidies.

Because of the data extraction limits, 15 cities were selected based on propensity score constructed using logit regression of license plate treatment on city-level characteristics such as GDP per capita and average salary level. The inherent assumption made is that there will be no explained heterogeneity besides these observed characteristics. The detailed selection of cities are listed in Table 4. The bold cities are the ones chosen in our regression and the red highlighted ones are cities with licence plate treatment. As in many empirical studies using China's regional data, we excluded cities such as Lasa (part of Tibet) and Urumqi (part of Xinjiang) because these are autonomous regions with different economic makeup and different ethic majority, which may include unobserved heterogeneities. In addition, since we tested a trial regression with four initial cities such as Xian, Zhengzhou and Chengdu, we included them in our final recreational analysis even though they may not be the most similar to the attributes of the cities with license plate restrictions.

5 Empirical Model and Analysis

5.1 Model

To evaluate the effectiveness of the policy, it is natural to apply panel regressions since our data in in the city–month unit and the policy variable is continuous in time. That said, our central model is,

$$Y_{it} = \alpha_i + \tau_t + \beta Policy_{it} + \sum_k \theta_k X_{it}^k + \epsilon_{it}, \tag{1}$$

where Y_{it} is the lof sales of EV; α_i and τ_t are city and time fixed effects; $Policy_{it}$ is the subsidy in tens of thousands of Chinese Yuan (equivalent to roughly \$1,600); X_{it}^k stands for a collection of city-level control variables such as the one-period lag of EV sales, GDP per capita (in log), population (in log), average salary (in log), and the number of local charging stations.

As a preliminary check, Figure 8 displays the distribution of local subsidies of all the 15 cities in our sample. We could see that the mean is close to 80,000 Yuan, and there exists substantial variation in the subsidy intensity, which grants accurate standard error estimation.

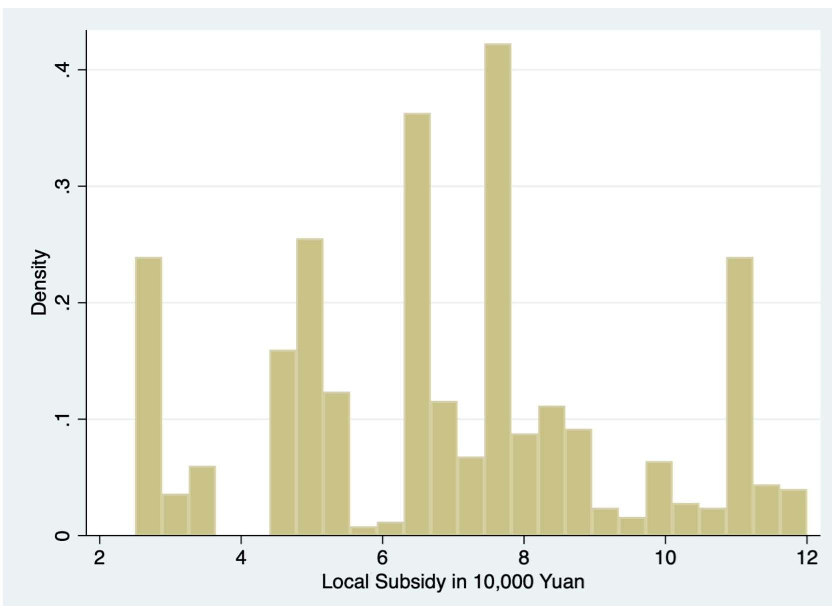

Figure 8: Distribution of Local Subsidy (in 10,000 Yuan)

5.2 Main Regression Results

Table 1 illustrates our regression estimates. All six columns share the same response variable, i.e., log of EV sales, and they differ by the regression setup. Particularly, columns (1), (2), and (3) are regular panel regressions without IV, and the (4), (5), (6) are with IV being the percentage of local subsidy compared to the national subsidy.

VARIABLES	(1) levsales	(2) levsales	(3) levsales	(4)-IV levsales	(5)-IV levsales	(6)-IV levsales
Total Subsidy	0.10815***	0.09860***	0.05975***	0.08630***	0.08630***	0.06068**
	(0.02643)	(0.02559)	(0.02033)	(0.03216)	(0.03216)	(0.02471)
Lag EV Sales		0.21895***	0.32091***			0.32076***
		(0.03230)	(0.03234)			(0.03199)
Charging Poles	-0.00003***	-0.00002***	-0.00003***	-0.00004***	-0.00004***	-0.00003***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Log GDP percapita	1.37008***	1.22836***	0.37664	1.36908***	1.36908***	0.37385
	(0.06724)	(0.06846)	(0.34217)	(0.06702)	(0.06702)	(0.34040)
Log Population	0.38453	0.37099	-0.07650	0.27742	0.27742	-0.07210
	(1.25147)	(1.21119)	(0.93310)	(1.25055)	(1.25055)	(0.92325)
Log Mean Salary	8.68463***	6.71749***	7.04490***	8.47470***	8.47470***	7.05776***
	(0.78039)	(0.80808)	(0.75553)	(0.79773)	(0.79773)	(0.77193)
Constant	-97.86277***	-76.52686***	-77.56512***			
	(8.41723)	(8.71633)	(8.17514)			
Observations	660	659	659	660	660	659
R-squared	0.51097	0.54394	0.73415	0.51045	0.51045	0.73415
Number of citycode	15	15	15	15	15	15
City FE	YES	YES	YES	YES	YES	YES
Month FE	YES	NO	YES	YES	NO	YES
Lag	NO	YES	YES	NO	YES	YES
Month	NO	NO	YES	NO	NO	YES
IV	NO	NO	NO	YES	YES	YES

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

Table 1: Panel Regression Results

To interpret the result, we start from column (1), the baseline model without IV, lag of EV sales, or monthly dummies. Our coefficient of interest is around 0.108, suggesting a 10,000 Yuan increase in purchasing subsidy could boost about 11% of the EV sales. The effect is immense, but the scale could make sense because a 10,000 Yuan subsidy would be equivalent to roughly two to three months of the disposable income of an average consumer in China.

Next, we add step-by-step the lag of EV sales and the monthly dummies, which give the results of (2) and (3) respectively. In fact, the estimated coefficient of the subsidy declines, which suggests the presence of the omitted variable bias in (1). It turns out that, with the full set of controls in (3), an additional 10,000 Yuan subsidy would increase EV sales by 6.2%. This is not widely different from our baseline model, which suggests the robustness of our estimations.

Based on the regular panel regressions in (1), (2), and (3), we implement three sets of IV (the percentage of local subsidy compared to national subsidy) regressions accordingly. To compare the results, (1) and (4), (2) and (5), as well as (3) and (6) are the three pairs. To interpret the numbers, the estimates in (4) and (5) are close, and they amount to say that an extra 10,000 Yuan subsidy would promote the EV sales by around 8.9%. Adding monthly dummies in (6) would shrink the estimates, but the magnitude remains to around 6.25%. Overall, our estimation, indicating the robustness of the coefficients.

Note that in all three IV regressions, our models significantly pass the Stock-Yogo weak identification test provided by the xtivreg2 command in Stata.

In terms of other interesting control variables, we see that both GDP per capita and salaries have strong positive effect on EV sales. This could be because residents in more affluent regions tend to be more open to new consumption choices as in this EV case. Population seems not to have much correlation with the EV sales, while it could be greatly related to regular car purchases. This might suggest that EV has not yet become a typical durable consumption choice.

One puzzling finding is the negative coefficient of the number of charging stations. From the sign, it seems that more charging stations would discourage EV purchases. However, the magnitude is negligible. This means, in effect, charging stations barely have any influence on EV purchases from 2016 to 2019. This is in accordance with many of the narrative evidences that we saw in the news, which typically says that most of the charging stations were not being used during this period.

In addition, we also want address that we have tried out the other IV options as discussed in previous section. However, either they fail to pass the weak identification test, or they lead to explosion of the coefficients of interest. For example, using total car ownership as an IV, the model says that an additional 10,000 Yuan subsidy would lead to 50% increase in EV sales.

5.3 Regression Results for Six Major Cities

As outlined in the policy section, there are six cities in China that have implemented automobile purchase restrictions and have exempted these restrictions for EVs. The purchase restrictions are implemented to curtail pollution as well as reduce traffic congestion. Hence these cities are intrinsically different, as shown in 2 below:

Table 2: Balance Test for Regulated (6) and Non-regulated cities (28)

	(1)	
GDP per capita	-4.800***	(0.365)
Average Salary	-34480.6***	(1392.0)
Average Housing Value	-6.079***	(0.602)
Car Ownership per capita	-0.0728***	(0.00684)
Charging station per capita	-9.121***	(0.647)
Tax Revenue per capita	-1.696***	(0.0903)
Tax Expenditure per capita	-1.149***	(0.122)
N	1496	

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

These six cities have higher GDP per capita, have more cars per person, and are more densely populated. If we restrict our samples to only include these six cities, the subsidy regressor has a less significant coefficient, as shown in 3. However, we are unsure whether such decrease in the subsidy effect is due to the purchase restriction policies or other unobserved factors. For example, the city Beijing, Shanghai, Guangzhou, Shenzhen are considered destination for college graduates first job. Residents living in these cities may be rich enough to care less about subsidies, or they are more open minded to adopt an EV for their first automobile.

VARIABLES	(1) levsales	(2) levsales	(3)-IV levsales	(4)-IV levsales
Total Subsidy	0.06662*	0.04857	0.03672	0.04193
	(0.03548)	(0.03065)	(0.04343)	(0.04217)
Lag EV Sales	0.28625***	0.45003***	0.28772***	0.45205***
	(0.05232)	(0.04888)	(0.05179)	(0.04811)
Charging Poles	-0.00003***	-0.00003***	-0.00004***	-0.00003***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Log GDP percapita	1.01472***	-0.00728	1.01443***	0.04303
	(0.10254)	(0.41660)	(0.10148)	(0.46242)
Log Population	0.73273	0.21053	0.64767	0.19540
	(1.18482)	(0.82612)	(1.17482)	(0.80133)
Log Mean Salary	6.70905***	6.52862***	6.39040***	6.45387***
	(1.40158)	(1.03323)	(1.41358)	(1.05419)
Constant	-79.21248***	-74.10477***		
	(14.71785)	(10.89676)		
Observations	263	263	263	263
R-squared	0.54015	0.78688	0.53885	0.78684
Number of citycode	6	6	6	6
City FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Lag	YES	YES	YES	YES
Month	NO	YES	NO	YES

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

Table 3: Panel Regression Results

6 Other Concerns and Future Studies

Here we want to highlight some potential issues in our study and shed lights on future directions for remedy.

1. While we have city-month level of demand data for different car makes, we did not utilize this data in our subsidy analysis. Instead, we utilized the maximum consumer subsidy outlined in the policy document in a given period of time. In the future, we could exploit this dataset further to see the effects of subsidies on different ranges of electric vehicles

2. Since we are using a two-way fixed effect model, the inherent assumption is that there are no city-level time-varying unobservables. However, the difficulty of this project is the concurrences of multiple experimental policies towards electric vehicle, which invalidate the inherent assumptions to recover a valid identification. Although we choose a time period of relative stable policies (focused on consumer-based EV adoption), we are unsure of the policies implemented at the local level that are not documented. In fact, when collecting local level policy documents, we have to look for archived documents in industrial association websites.

In the future, we may rely on web scraping to collect a more comprehensive list of policy interventions.

3. One the major challenge in constructing the policy variable is the uncertainties in local policy directions. It difficult to set local policies if the central policy is constantly changing. There are countable incidences that the policies regarding 2017 subsidies are only published more than a year later. Hence for the year 2017, consumers are unsure of what the subsidy would be and could only conjecture from previous policy documents. On area of study could be the anticipation effects under policy uncertainties.

4. It is widely noted that policies favor local protection. While there are published documents on consumer EV subsidies, not all EV can be subsidized. As outlined in the policy section, only the car types outlined in the published 'catalogue' are eligible for subsidies. One future direction could be to look at the local protection happening both at the national level as well as the prefectural level.

5. When looking at the sales data, we realized that the sales of EV are highly correlated with local automobile industrial clusters. If a brand is considered 'local', the brand will be sold favorably in that particular local region. In addition, the sales of EV will be higher in a automobile industrial cluster. In China, there are six automobile industry clusters, it would be interesting to explore this cluster effect with EV demand.

7 Conclusions

Industrial policies targeting around EV have been a hot topic in recent decades. In this project, we carefully choose a sample of Chinese cities as well as the associated time window, and attempt to estimate the effect of the mainstream policy practice – the purchasing subsidy. Our project is also the first to study the effect of subsides on demand during a time when the subsidy is phasing-out and the market for electric vehicles are maturing.

In the empirical part, we are aware of the potential endogeneity issues and come up with several candidate IVs trying to address them. While our IVs are not perfect, our regressions yield stable and sensible estimates revealing that an extra 10,000 Yuan subsidy would help to boost around 6% to 11% of EV sales. As the policy combo related to EV becomes increasingly complex in China and other areas in the world, future studies could look at the effect of an interaction of different policy tools. Also, it would be interesting to have finer data at consumer level to see the potential heterogeneous response of the agents given policy incentives.

8 Appendix

Table 4: Propensity Score Matching - City Selection

City	Province	Propensity Score	Blocks
Shenzhen	**Guangdong**	**.999786**	**100**
Beijing	**Beijing**	**.8599021**	**86.2**
Shanghai	**Shanghai**	**.853972**	**85.8**
Guangzhou	**Guangdong**	**.7176062**	**72.2**
Nanjing	**Jiangsu**	**.4179803**	**42.2**
Hangzhou	**Zhejiang**	**.3425273**	**34.6**
Ningbo	**Zhejiang**	**.2980265**	**30.4**
Xiamen	**Fujian**	**.2902811**	**29.6**
Wuhan	**Hubei**	**.1609144**	**16.6**
Lasa	Tibet	.1452899	14.8
Changsha	**Hunan**	**.1290923**	**13.4**
Tianjin	**Tianjin**	**.1114722**	**11.8**
Qingdao	**Shandong**	**.1049454**	**10.8**
Urumqi	Xinjiang	.067172	7.4
Dalian	Liaoning	.0579101	6.2
Jinan	Shandong	.0559355	6
Hefei	Anhui	.036836	4.2
Chengdu	**Sichuan**	**.0361162**	**4.2**
Fuzhou	Fujian	.0356939	4.2
Zhengzhou	**Henan**	**.0340392**	**3.8**
Hohhot	Inner Mongolia	.025001	2.8
Yinchuan	Ningxia	.0249007	3
Kunming	Yunnan	.0242514	3
Xian	**Shaanxi**	**.0218651**	**2.6**
Nanchang	Jiangxi	.0207893	2.4
Guiyang	Guizhou	.0189356	2.4
Taiyuan	Shanxi	.0182757	2.4
Shenyang	Liaoning	.0149005	2
Changchun	Jilin	.0146324	2
Lanzhou	Gansu	.0141925	2
Haikou	Hainan	.0121369	1.6
Xining	Qinghai	.0083574	1.4
Chongqing	Chongqing	.008334	1.4
Nanning	Guangxi	.0071321	1.2
Harbin	Heilongjiang	.0056532	1
Shijiazhuang	Hebei	.0051433	1

Signing Date	File Reference No.	File Name	Applicable	Policy Highlights	Policies
2015.04.22	Caijian [2015] No.134	2016 New Energy Vehicle Promotional Subsidy Standard	2016.01.01-2020.12.31	Set the subsidy for the year 2016, and year 2017 and 2018 will be 20% less than year 2016; year 2019 and 2020 will be 40% less than year 2016.	BEV Subsidy: •$100 \le R < 150$: 2.5 •$150 \le R < 250$: 4.5 •$R \ge 250$: 5.5
2016.12.29	Caijian [2016] No.958	Notice on Adjusting the Financial Subsidy Policy for the Promotion and Application of New Energy Vehicles	2017.01.01-2020.12.31	Under the premise of maintaining the overall stability of the subsidy policy from 2016 to 2020, adjust the subsidy standards for new energy vehicles. **The local fiscal subsidies (the sum of local fiscal subsidies at all levels) shall not exceed 50% of the central fiscal subsidies**. Year 2019 and 2020 will be 40% less than this standard.	BEV Subsidy: •$100 \le R < 150$: 2 •$150 \le R < 250$: 3.6 •$R \ge 250$: 4.4
2017.12.26	Caizhengbu [2017] No.172	Announcement on the exemption of new energy vehicle purchase tax	2018.01.01-2020.12.31	From January 1, 2018 to December 31, 2020, the purchase of new energy vehicles will continued to be exempted from vehicle purchase tax. For new energy vehicles that are exempt from vehicle purchase tax, management is implemented through the issuance of the "Catalogue of New Energy Vehicle Models Exempted from Vehicle Purchase Tax" (hereinafter referred to as the "Catalogue").	Purchase Tax Exemption
2018.02.12	Caijian [2018] No.18	Notice on Adjusting and Improving the Financial Subsidy Policy for the Promotion and Application of New Energy Vehicles	2018.02.12-2018.06.11	The new energy vehicle subsidy standard has been adjusted and further refined. This notice will be implemented from **February 12, 2018 to June 11, 2018 It is a transitional period**. Vehicles registered during the transition period that meet the requirement of 2017 technical indicators but not the 2018 technical indicators will be subsidized 0.7 times of the corresponding standard in (Caijian [2016] No.958).	BEV Subsidy: •$150 \le R < 200$: 1.5 •$200 \le R < 250$: 2.4 •$250 \le R < 300$: 3.4 •$300 \le R < 400$: 4.5 •$R \ge 400$: 5
2019.03.26	Caijian [2019] No.138	Notice on Further Improving the Financial Subsidy Policy for the Promotion and Application of New Energy Vehicles	2019.03.26-2019.06.25	**The transition period is from March 26, 2019 to June 25, 2019.** During the transition period, vehicles that meet the requirement of 2019 technical indicators will be subsidized 0.6 times of the corresponding standard in (Caijian [2018] No.18). **Local governments should no longer provide subsidies for the purchase of new energy passanger vehicles after the transition period**.	BEV Subsidy: •$250 \le R < 400$: 1.8 •$R \ge 400$: 2.5

Figure 9: Central Government Subsidy and Tax Policies (2016-2019)

References

D. Diamond. The impact of government incentives for hybrid-electric vehicles: Evidence from US states. 37(3):972–983. ISSN 0301-4215. doi: https://doi.org/10.1016/j.enpol.2008.09.094. URL https://www.sciencedirect.com/science/article/pii/S0301421508005466.

O. Egbue and S. Long. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. 48:717–729. ISSN 0301-4215. doi: 10.1016/j.enpol.2012.06.009. URL https://www.sciencedirect.com/science/article/pii/S0301421512005162.

U. Gneezy, S. Meier, and P. Rey-Biel. When and why incentives (don't) work to modify behavior. 25(4):191–210. doi: 10.1257/jep.25.4.191. URL https://www.aeaweb.org/articles?id=10.1257/jep.25.4.191.

A. Jenn, I. L. Azevedo, and P. Ferreira. The impact of federal incentives on the adoption of hybrid electric vehicles in the united states. 40:936–942. ISSN 0140-9883. doi: https://doi.org/10.1016/j.eneco.2013.07.025. URL https://www.sciencedirect.com/science/article/pii/S0140988313001709.

S. Li and A. Beresteanu. Gasoline prices, government support and the demand for hybrid vehicles in the u.s. URL https://rosap.ntl.bts.gov/view/dot/38280.

A. C. Mersky, F. Sprei, C. Samaras, and Z. S. Qian. Effectiveness of incentives on electric vehicle adoption in norway. 46:56–68. ISSN 1361-9209. doi: https://doi.org/10.1016/j.trd.2016.03.011. URL https://www.sciencedirect.com/science/article/pii/S1361920916000407.

W. Sierzchula, S. Bakker, K. Maat, and B. v. Wee. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. 68:183–194. ISSN 0301-4215. doi: https://doi.org/10.1016/j.enpol.2014.01.043. URL https://www.sciencedirect.com/science/article/pii/S0301421514000822.

J. Struben and J. D. Sterman. Transition challenges for alternative fuel vehicle and transportation systems. 35(6):1070–1097. ISSN 0265-8135. doi: 10.1068/b33022t. URL https://doi.org/10.1068/b33022t. Publisher: SAGE Publications Ltd STM.

M. Tran, D. Banister, J. D. K. Bishop, and M. D. McCulloch. Realizing the electric-vehicle revolution. 2(5):328–333. ISSN 1758-6798. doi: 10.1038/nclimate1429. URL https://www.nature.com/articles/nclimate1429. Number: 5 Publisher: Nature Publishing Group.

N. Wang, H. Pan, and W. Zheng. Assessment of the incentives on electric vehicle promotion in china. 101:177–189, a. ISSN 0965-8564. doi: https://doi.org/10.1016/j.tra.2017.04.037. URL https://www.sciencedirect.com/science/article/pii/S0965856416309193.

S. Wang, J. Wang, J. Li, J. Wang, and L. Liang. Policy implications for promoting the adoption of electric vehicles: Do consumer's knowledge, perceived risk and financial incentive policy matter? 117:58–69, b. ISSN 0965-8564. doi: https://doi.org/10.1016/j.tra.2018.08.014. URL https://www.sciencedirect.com/science/article/pii/S0965856418301186.

J. Xiao, X. Zhou, and W.-M. Hu. Welfare analysis of the vehicle quota system in china. 58(2):617–650. ISSN 1468-2354. doi: https://doi.org/10.1111/iere.12229. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/iere.12229. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/iere.12229.

S. Yeh. An empirical analysis on the adoption of alternative fuel vehicles: The case of natural gas vehicles. 35(11):5865–5875. ISSN 0301-4215. doi: 10.1016/j.enpol.2007.06.012. URL https://www.sciencedirect.com/science/article/pii/S0301421507002534.

X. Zhang, X. Bai, and H. Zhong. Electric vehicle adoption in license plate-controlled big cities: Evidence from beijing. 202:191–196, a. ISSN 0959-6526. doi: https://doi.org/10.1016/j.jclepro.2018.07.265. URL https://www.sciencedirect.com/science/article/pii/S0959652618322546.

X. Zhang, Y. Liang, E. Yu, R. Rao, and J. Xie. Review of electric vehicle policies in china: Content summary and effect analysis. 70:698–714, b. ISSN 1364-0321. doi: https://doi.org/10.1016/j.rser.2016.11.250. URL https://www.sciencedirect.com/science/article/pii/S1364032116310309.