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An Empirical Assessment of the Impact of Subsidies on EV adoption in China: A Difference-in-Differences Approach

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Abstract

It is widely recognized that Electric vehicles (EVs) will play a crucial role in the electrification of transport, which is necessary for reaching a net-zero emissions economy. This recognition is reflected in the number of initiatives introduced worldwide to promote the EV industry, ranging from purchase subsidies to the provision of charging infrastructure and direct industry assistance. In this context, the Chinese government introduced a comprehensive program of government subsidies to support the sale of EVs. This paper estimates the impacts of these subsidies on EV sales in China using the difference-in-differences (DID) and propensity score matching (PSM) approach. Based on the panel data at city level from 2009 to 2018, we show that subsidies were the major contributor to the increase in EV sales. Our results suggest that the provision of infrastructure such as charging piles is also an important contributing factor. These findings are robust across model specifications and regression approaches. The heterogeneity analysis indicates that the treatment effect is heterogeneous across EV types, city sizes and regions. Our results provide empirical support for the current policy settings designed to promote EV sales in China.

JEL classification: Q48, C13, C54.

Keywords: Electric vehicles, subsidy policies, difference-in-differences approach, China.

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1 Introduction

The path to decarbonizing the economy involves first greening the electricity sector, and then electrifying transport and industry. Electric Vehicles (EVs) will play a direct role in reducing emissions by electrifying transport (Rezvani et al., 2015; Huang and Qian, 2018; Shim et al., 2018). Also, EVs can become virtual power plants, store electricity when there is excess solar generation, and can be used for power regulation purposes (Kempton and Letendre, 1997; Mwasilu et al., 2014; Wolinetz et al., 2018).

The importance of the role that EVs will play in decarbonization is evidenced by the myriad of initiatives introduced worldwide to promote the EV industry. These include the Partnership for a New Generation of Vehicles Program in the United States, the Road Map for Electrified Transportation in the European Union and the Energy Conservation and New Energy Vehicle Industry Development Plan[1] (Li et al., 2020). Despite these different initiatives, the market share of EVs in countries such as the US, France, Germany, and China remains well below 5% (China Automotive Technology and Research Center et al., 2020). This paper aims to shed light on the reasons for the uptake of EVs in China by estimating the impact of government subsidies on purchases of new EVs. It complements existing studies by exploring the causal relationship between existing subsidies and EV sales.

The Chinese government support for the EV industry can be traced back to at least 2001, with the introduction of direct financial support for the industry itself, the provision of infrastructure, R&D, and the development of human resources (Zhang et al., 2017). From 2009, the Chinese government complemented its financial support to the supply side with a demand side approach which entailed providing subsidies which provided support for the demand side by subsidizing private purchases of EVs. From 2016, many local governments introduced their own subsidies to promote EV development in addition to the subsidies provided by the central government.

Following the introduction of such extensive support policies, China's EV industry has evolved at a fast pace. According to the Automobile Industry Association in China (AIAC), the production of EVs increased by 65.6% and 60.5% in 2017 and 2018 respectively, and sales of EVs also increased by 69.1% and 58.7% in 2017 and 2018 respectively.[2] According to the Ministry of Industry and Information Technology (MIIT) of China, the production and sales of EVs reached 1.105 and 1.115 million in 2020 respectively, reflecting increases of 5.4% and 11.6% relative to 2019.[3] More details about the trend of EV sales in China can be found in Figure 1.[4]

[1]This has been followed by the New Energy Vehicle Industry Development Plan (2021-2035). See https://climatecooperation.cn/climate/new-energy-vehicle-industry-development-plan-2021-2035/.

[2]The absolute number of EV production was 472,512, 782,624 and 1,255,856 in 2016, 2017 and 2018, respectively, and those of EV sales were respectively 464,708, 768,023 and 1,247,514 in the three years between 2016 and 2018.

[3]See `http://paper.cnii.com.cn/article/rmydb_15824_298908.html`.

[4]Note that the growth rate of EV sales before 2011 is not given in the figure, as the number is too large relative to interval values shown in the right vertical line—over 4100% in 2010.

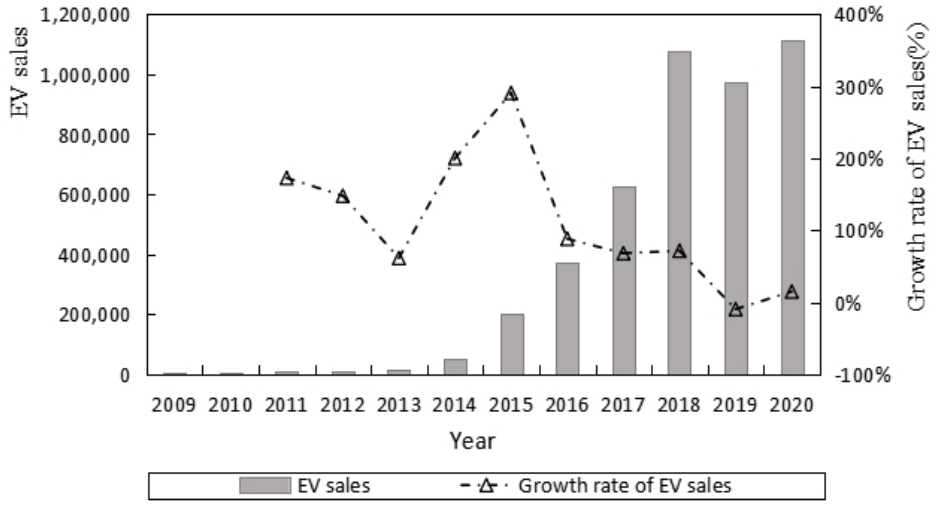


Figure 1: Trend of EV Sales in China

Data source: The data between 2009-2018 are from *China Energy Saving and New Energy Vehicle Yearbook*, and the data of 2019 and 2020 are from the Ministry of Industry and Information Technology (MIIT) of China.

The impressive growth of the EV industry in China has stalled for several reasons. First, the Chinese government substantially reduced the subsidies to EVs from 2018. This followed from fraudulent claims of subsidies through inflated sales and production figures.[5] This led to a reduction in the production and sales of EVs in 2019 of 2.3% and 4%, respectively. In particular, the sales of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) decreased by 1.2% and 14.5% respectively.[6] The outbreak of the COVID-19 pandemic, and the resulting impact on the global and Chinese economies has further reduced EV sales in China in the first half of 2020. EV sales were further impacted by the Chinese government's decision to promote the sales of conventional vehicles, as part of its stimulus policies to support the economy during the pandemic.

The slowdown in the production and sales of EVs will make it difficult to achieve the ambitious goal of increasing the share of EVs in new vehicle sales to 20% in 2025. It would also make it difficult for China to ban the manufacture and sales of conventional vehicles in the near future.[7] The challenging environment for EVs is likely behind the Chinese government's extension of subsidies and of a range of favorable treatments to the end of 2022.[8] This extension was accompanied by a set of policies designed to promote EV sales in rural areas.[9] Perhaps

[5]Subsidies are paid to manufacturers only for the EVs that have been sold (not just produced). To secure the receipt of subsidies, some manufacturers sold their vehicles to themselves rather than to end-users (Yan et al., 2018; Li et al., 2019).

[6]See `http://www.xinhuanet.com/fortune/2020-01/14/c_1125457919.htm`

[7]A future potential ban was flagged by the Ministry of Industry and Information Technology, in the second half of 2017.

[8]For more details, see *China announced 2020–2022 subsidies for new energy vehicles*.

[9]The notice on 'Going to the countryside' was jointly issued in July 2020 by China's Ministry of Industry and Information Technology, Ministry of Agriculture and Rural Affairs, and Ministry of Commerce. See `http://www.gov.cn/xinwen/2020-07/15/content_5527050.htm`.

not surprisingly, EV sales in China recovered in the second half of 2020, increasing by 72%, in contrast to the decrease of 43% in the first half of the year.[10]

Despite the government's seemly ambivalent approach to EV subsidies, it is generally accepted that they are necessary to promote the uptake of EVs. Ownership costs of EVs, relative to conventional vehicles, are very high (Zhang et al., 2017).[11] Subsidies may also counter other disadvantageous features of EVs such as the limited range and the lifetime of batteries. It is expected, however, that subsidies may become unnecessary once manufacturing and ownership costs fall (Hao et al., 2014)

In this paper, we use data from 286 prefecture-level cities (2009-2018) to empirically test the proposition that subsidies actually promote the sales of EVs. Under both a Difference-in-Difference (DID) approach and a Propensity Score Matching (PSM) approach, we find that subsidies have played a significant role in promoting the uptake of EVs. In particular, on average for the period under analysis, approximately one quarter of the annual increase in EV sales in China can be attributed to the existence of subsidies. We estimate that the subsidies led to an average increase on annual sales of 120%, whereas sales have increased approximately 500% annually from 2009 to 2018. The estimation results also show that the construction of infrastructure such as charging piles has also played a significantly positive role. Moreover, EV sales are also affected by factors such as economic development level, gasoline prices and restrictions on the ownership of conventional vehicles. These findings are robust across various model specifications and identification approaches.

We have also analyzed how the EV subsidy policies impact the different types of EVs. We find that the impact is heterogenous. For example, the subsidy policy has incentivized the sales of battery electric vehicles (BEV) the most, relative to other types of EVs such as plug- in hybrid electric vehicles (PHEV) and extended-range electric vehicles (EREV). The treatment effects of this policy are also diverse across distinct cities and regions.

The remainder of this paper is organized as follows. Section 2 reviews related studies. Section 3 briefly describes the evolution of EV subsidy policies in China. Section 4 presents the data and introduces our econometric approach. Section 5 presents the estimation results, including our robustness checks. Section 6 examines the impact of subsidies across the different types of EVS and across distinct cities and regions. Finally, Section 7 draws our main conclusions and provides some policy implications.

2 Literature Review

The perceived slow uptake of EVs has led to a substantive research effort to understand the impact of social-psychological and policy factors on individuals' purchasing decisions. Psychological attributes related to EV purchases include attitude, subjective norms, and perceived

[10]More details see `https://auto-time.36kr.com/p/1065750506399106`.

[11]The ownership cost of EVs includes purchasing cost, operating and maintenance costs and a lower resale value compared to conventional vehicles.

behavioral control (see, for example, Liao et al., 2017; Du et al., 2018). Policy attributes include purchase subsidies, tax breaks, preferential access to charging, driving restrictions and license plate controls (see, for example, Li et al., 2020). Liao et al. (2017) reviewed this literature, which is based on surveys, to ascertain the various factors that influence consumers' decision to purchase an EV.

This literature tends to point to financial incentives, such as purchase subsidies, not being instrumental in such a decision. For example, Wang et al. (2018) used data from a survey of 320 Chinese consumers and found that financial incentives had no significant effect on intention to adopt EVs. Ye et al. (2021) conducted a comprehensive study combining psychological factors obtained through a survey with 1087 responses from individuals from 29 provinces and 206 cities in China, with socio-economic data and the different policies that support the uptake of EVs. These authors showed that high purchase intentions are characterized by the existence of at least one psychological attribute. Importantly, their results showed that even when the government had implemented purchase subsidies, the joint absences of attitude, subjective norms, and perceived behavioral control resulted in low EV purchase intention.

These results raise an important policy question. The Chinese government currently spends 37.5 billion RMB a year subsidizing such purchases and, therefore, ascertaining their effectiveness in promoting EV adoption is a crucial step in determining the optimal policy mix – the combination of financial incentives, investment in infrastructure, advertisement, etc.[12] Our contribution is to provide an empirical assessment of the impact of subsides by using a revealed preference approach. That is, our empirical assessment is based on actual sales, rather than based on intentions to buy. It complements the existing literature based on surveys, which is useful to understand perceived barriers to EV adoption, by assessing the causal relationship between subsidies and actual purchases.

Our paper also contributes to a literature that empirically assesses the overall influence of various policy incentives and related socio-economic factors on EV adoption by using sales data (e.g., Sierzchula et al., 2014; Langbroek et al., 2016). Rezvani et al. (2015) have surveyed this literature. This literature can be split into two strands. The first stand focuses on the impact of the various existing policies on the uptake of EVs across China using a variety of methodologies (e.g., Ma et al., 2017; Li et al., 2019; Dong and Liu, 2020). For example, Li et al. (2019) used a complex network evolutionary game method to explore the dynamic impacts of government policies on EV diffusion and chose BYD, the leading new energy vehicle manufacturer, as a case study for China's EV industry.

Using a multivariate co-integration model and an error correction model, Ma et al. (2017) showed that EV purchase subsidies, tax exemptions, the restriction of conventional vehicles and the abolition of traffic restrictions all significantly led to the increase of EV market share. In particular, the significantly positive effect of purchasing subsidies is consistent with the findings by Zhang et al. (2011) and Yang et al. (2019).

The second strand of the literature focuses on the impact of specific policies or pilots (e.g.,

[12] See `http://www.cada.cn/Trends/info_90_7874.html`.

Ou et al., 2018; Qiu et al., 2019; Chi et al., 2020). For instance, based on the monthly data of 88 pilot cities for EV development from January 2014 to August 2015, Qiu et al. (2019) found charging discounts and infrastructure construction subsidy significantly promoted EV sales, whereas the impact of purchase subsidies policies was insignificant. Chi et al. (2020) estimated the impact of the license plate quota policy for conventional vehicles on EV adoption. They showed the license plate quota policy can significantly increase the annual sales of EVs in Tianjin, Hangzhou, Shenzhen, and Haikou by approximately 73.4%, 87.5%, 87%, and 65.5% respectively. Ou et al. (2018) evaluated the impacts of a dual-credit policy on the sales of plug-in EVs in China. By simulating different policy scenarios, they found that the dual-credit policy played a significant role in the development of EV industry.

The literature reviewed above provides mixed evidence on the impact of subsidies on the sale of EVs. Different methodologies, specific datasets, or policy initiatives (e.g., pilots), and short periods of analysis make it difficult to assess the literature. For example, it is unclear how to compare the contradictory findings of Ma et al. (2017) and Qiu et al. (2019) with respect to the effectiveness of different policies. Our contribution to this literature is to provide a comprehensive study of the impacts of purchase subsidies on EV sales based on the data from 286 Chinese cities, covering the period 2009 to 2018. Moreover, by applying a counterfactual research method (difference-in-differences—DID), we are able to establish a causal relationship between subsidies and sales. In addition to a series of robustness checks, we also provide a detailed heterogeneity analysis for the different types of EVs, city tiers and regions.

3 The Evolution of EVs Subsidy Policy

China began to promote the sale of EVs on a trial basis in 2009 by providing price subsidies and tax incentives. Since then, the subsidy policy for China's EV industry has progressed through three stages, as shown in the timeline in Figure 2.

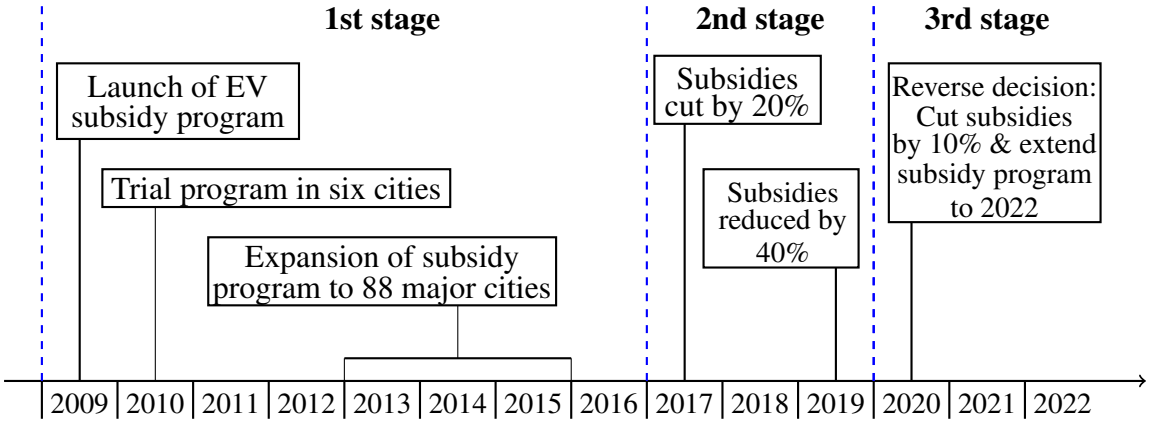


Figure 2: Timeline of China's Subsidy Policies for EVs

Starting in 2009, the first stage saw the gradual introduction of EV subsidies, which were extended from EVs for public transport to those for private use, and from pilot cities to nation-

wide. The "Ten Cities and Thousand Vehicles" program was introduced jointly by the Ministry of Finance (MoF) and the Ministry of Science and Technology in 2009. This program aimed to subsidize EVs used in public transport. In 2010, six cities (Beijing, Shanghai, Changchun, Shenzhen, Hangzhou and Hefei) were selected as pilots for a program subsidizing privately purchased EVs. With the support from the MoF and other government departments, the private purchase EV subsidies were expanded to more cities in 2013, and by 2015, 88 major cities had been included in the program. These subsidies were then implemented nationwide in 2016, with the issue of "*Notice on the financial support for the promotion and application of new energy vehicles from 2016 to 2020*". In addition to subsidies, the government also introduced preferential consumption tax rates, and vehicle and vessel tax and vehicle purchase tax reductions and exemptions. The Chinese government also supported the construction of infrastructure, such as charging facilities, in the pilot cities. In some places such as Shanghai, EVs are exempt from car registration fees.[13]

The second stage of the policy saw a reduction in the subsidies for individual EV purchases, while the total level of subsidies was still expanding as demand for EVs increased. The reduction in the subsidies during this period is illustrated in Table 1. According to the *Notice on the Financial Support Policy for New Energy Vehicles in 2016-2020*, subsidy standards for other vehicle models except fuel cell vehicles would be reduced between 2017 and 2020. In particular, compared to the 2016 level, subsidies were reduced by 20% in both 2017 and 2018, and were scheduled to be reduced by a further 40% in 2019 and 2020. Subsidies from local governments had been suspended from 2019, and all subsidies for EVs were to be canceled from 2020. In addition, the requirements for the driving range and energy efficiency of vehicles were raised (e.g., the minimum driving range of EVs to qualify for the subsidy increased from 100 kilometers in 2017 to 250 kilometers in 2019).

Table 1: Subsidies per vehicle type

EV Types	**Driving Range** (kms)	**Subsidies** (RMB)		
		2017	**2018**	**2019**
BEVs	100 < range < 150	20,000	0	0
	150 < range < 200	36,000	15,000	0
	200 < range < 250	36,000	24,000	0
	250 < range < 300	44,000	34,000	18,000
	300 < range < 400	44,000	45,000	18,000
	range $\geq$ 4000	44,000	50,000	25,000
HPEVs	range $\geq$ 50	24,000	22,000	10,000

In the third stage, from April 2020, the Chinese government extended the subsidies program, due to expire at the end of 2020, through to 2022. This largely stems from a desire to stimulate the EV market amid the global recession. As in previous adjustments, the subsidy amounts

[13] See `https://www.argusmedia.com/en/news/2185607-chinas-shanghai-continues-to-offer-free`

per vehicle type were scaled down, with a reduction of 20% in 2021 and 30% in 2022.[14] In addition, to qualify for the subsidies, the cost of EVs (with taxes included) should be lower than RMB 300,000 (USD 42,362).[15]

4 Data and Methodology

4.1 Data Description

This section briefly describes the sources of data and the construction of variables. EV sales are from *China Energy Saving and New Energy Vehicle Yearbook* (CESNEV). The EV subsidy policy information is collected from the National Development and Reform Commission (NDRC), Ministry of Industry and Information Technology (MIIT), Ministry of Finance, and Ministry of Transport.[16]

Table 2: Descriptive Statistics

Variables (unit)	Obs.	Mean	Std. Err	Min.	Max.
Dependent Variable					
Private EV sales	2,380	639.845	3,705.391	0	63,262
BEV sales	2,380	488.295	3,091.181	0	69,179
PHEV sales	2,380	165.662	912.578	0	19,739
EREV sales	2,380	99.297	1,320.882	0	36,781
Independent Variables					
EV subsidy policy	2,380	0.300	0.458	0	1
Control Variables					
Disposable income per capita (¥)	2,380	24,284.59	8,509.782	9,453	67,990
Population (10^3)	2,380	458.565	344.571	23.185	3,101.79
GDP (10^9 ¥)	2,380	2,307.208	3,271.359	104	33,106
Price of gasoline 92# (¥/ton)	2,380	8,968.448	961.574	7,530.083	10,064.75
Vehicle holdings (10^3)	2,380	429.13	592.16	11.69	5710.07
Number of charging piles	510	2714.180	11021.770	0	132,383
Vehicle ownership restriction	2,380	0.018	0.132	0	1

Note: As denoted in other parts of this paper, BEV, PHEV and EREV denote battery electric vehicle, plug-in hybrid electric vehicle, extended-range electric vehicle, respectively.

[14]Note that the subsidy policy for private EVs is different from that for commercial EVs, such as those used for public transport, taxis, ride-hailing service, sanitation vehicles, urban delivery, and postal vehicles. For these vehicles, subsidies will not be reduced in 2020. However, they will be cut by 10% in 2021 and 20% in 2022.

[15]This would imply that the Tesla vehicles made in China, as well as imported electric vehicles from BMW, Audi and Daimler do not qualify for subsidies. As a result, Tesla announced on April 30, 2020 that it would cut the pre-subsidy price of its standard-range Model 3 made in China from RMB 355,800 to RMB 291,800 to maintain eligibility.

[16]Beijing, Shanghai, Changchun, Shenzhen, Hangzhou and Hefei were selected as pilot cities for the subsidies program in 2010. From 2013, the program was expanded to more cities, and by 2015, 88 major cities had been covered. Since 2016, with the issue of "*Notice on the financial support for the promotion and application of new energy vehicles from 2016 to 2020*", the subsidy for EV purchase has been implemented nationwide.

We have also collected data on city characteristics that might have affected the selection of pilot cities, including disposable income per capita, population and GDP. In addition, three vehicle-related variables are also controlled for, including the price of gasoline, total number of vehicles in a city, and the number of charging piles in a specific place.[17] We also control for the existence of restrictions on licenses for conventional vehicles, as such restrictions can incentivize the purchase of EVs.[18]

The data of socio-economic variables (i.e., disposable income, population, GDP, and gasoline prices) are from the CEInet. Charging infrastructure information is from the CESNEV Yearbook, the NDRC, the MIIT, and the Economic and Information Technology Commission. The total number of vehicles in a city and the information about restrictive policies on vehicle ownership (i.e., the issuance of a vehicle license) are from *China Automotive Industry Yearbook* and the websites of governments at different levels.

All the data are provided at the city level. Our final sample includes 2,380 cities, after the elimination of outliers and the removal of cities for which crucial information was missing. The summary statistics of the data are given in Table 2.

4.2 Identification Methodology

4.2.1 Differences-in-differences

DID is a statistical technique that attempts to mimic an experimental research design using observational data by examining the differential effect of a treatment on a "treated group" versus a "control group" in a natural experiment. It estimates the effect of a treatment ((i.e., an explanatory variable) on an outcome (i.e., a dependent variable) by comparing the average change over time in the outcome variable for the treatment group, compared to the average change over time for the control group.

The selection of the control group is key for being able to apply a technique such as DID which relies on the construction of an appropriate counterfactual. However, the selection of the cities for the introduction of EV subsidies might not have been random. If this were the case, then it would not be appropriate to select the non-pilot cities as the control group because this would lead to biased estimation results. Hence, in this study we also use the DID approach to identify the treatment effects of the EV subsidy policy based on the matched data constructed with the propensity score matching (PSM) technique, as we explain next.

4.2.2 Propensity Score Matching

PSM allows one to estimate the effect of a treatment by accounting for the covariates that predict the treatment being received. It entails forming matched data of treated and control

[17] As for the gasoline price, we choose the representative yearly average price for unleaded gasoline 92#.

[18] Other supportive policies include the restrictions on the hours that conventional vehicles are allowed on urban roads and the increased access to carpool lanes to EV purchasers. We have not been able to control for the existence of such policies due to limited data availability.

groups that share a similar value of the propensity score (i.e., the probability of treatment assignment conditional on observed baseline characteristics). This method attempts to mimic a randomized controlled trial design.

To identify the treatment effect by PSM, the propensity score should be a balancing score; that is, conditional on the propensity score, the distribution of observed baseline covariates between treated and control groups needs to be similar. Hence, we will check the balancing property of the propensity score by comparing the means of the treated group and the control group, as shown in the balance test in subsection 5.3.1. The data between treated group and control group can be regarded as balanced if the difference between the means of the two groups is statistically small.

4.3 The Econometric Model

4.3.1 The Baseline Model

In a standard DID approach, where all the policy treatments are introduced at the same time, the econometric model would typically be written as:

$$EV_{it} = \alpha + \beta Policy_i + \gamma Time_t + \delta Time_t * Policy_i + \lambda Z_{it} + \varepsilon_{it} \tag{1}$$

where EV_{it} is the number of EV sales to private users in city i in year t, $Policy$ is the dummy variable indicating the EV subsidy policy, which is equal to 1 in the treated group and equal to zero in the control group. $Time$ is the time dummy variable, which is equal to one in the years after city i implements the EV subsidy policy and equals to zero otherwise. $Time * Policy$ is the interaction of time and policy, and its coefficient δ, the standard DID estimator, denotes the effect of the EV subsidy incentive policy on the sales of EVs. A positive and significant δ indicates that the EV subsidy policy exerts a positive effect on the sales of EVs. Z_{it} denotes a vector of time-varying city-level control variables. ε_{it} is the residual error term. As the data used are panel data, equation (1) is usually rewritten as follows:

$$EV_{it} = \alpha + \delta Time_t * Policy_i + \lambda Z_{it} + \nu_i + \tau_t + \varepsilon_{it} \tag{2}$$

where ν_i and τ_t are vectors of city and year dummy variables that account for the fixed effect of cities and time.

In our study, however, the subsidies were introduced to different places at distinct times. This requires us to modify the standard approach expressed in equation (2) to account a time-varying DID design as follows:

$$EV_{it} = \alpha + \beta Policy_{it} + \lambda Z_{it} + \nu_i + \tau_t + \varepsilon_{it}, \text{ i=1,...,286; t=2009,...,2018.} \tag{3}$$

where $Policy_{it}$ is the dummy variable indicating the EV subsidy policy, which is equal to 1 if city i is a pilot city for EV subsidy policy at time t. The coefficient β, the difference-in-

differences estimator, can be interpreted as the difference in EV sales of the pilot cities group relative to the control group. Z_{it} is the vector of control variables discussed above, including disposable income per capita, population, GDP, gasoline prices, vehicle ownership restrictions and quantity of charging piles. ν_i and τ_t are individual and time fixed effects. ε_{it} is the residual error term.

4.3.2 Strategy with Event Study Approach

To validate the identifying assumption that the trends are parallel for the pilot cities group and the control group absent the pilot EV subsidy policies, we employ a strategy that is similar to an event study methodology. This strategy entails estimating the following equation:

$$EV_{it} = \alpha + \sum_{\tau=-3}^{5+} \beta_\tau Policy_{i\tau} + \lambda Z_{it} + \nu_i + \tau_t + \varepsilon_{it} \tag{4}$$

Here, $Policy_{i\tau}$ is a set of dummies that equal to 1 if τ years have passed since city i had been selected as a pilot city for EV subsidy policy. The year when a city is selected as the pilot place for EV subsidy policy is left as the comparison group. If the coefficients β_{-k} (where $-k$ refers to k years before the implementation of EV subsidy policy) are not significantly different from 0, the parallel trends assumption, the prerequisite to conduct the DID approach, is likely to hold.[19] Exploiting the timing differences across waves of pilot cities, the model specification is similar to the event study strategy, as advocated by Altonji et al. (2005) and Jia (2014).

5 Results and Discussion

5.1 Preliminary Results

In the baseline specification, we run the regression with the full sample using the DID approach. The preliminary regression results, presented in Table 3 , reveal a high and statistically significant correlation between the EV subsidy policy and the sales of EVs in China across various regression specifications. Specifically, in columns (1) to (3) where the sample size is larger, the estimation results show that, due to the implementation of the EV subsidy policy, the EV sales increased by a large magnitude, around 180% per year on average over the sample period, and this result is significant at the one percent level. Given that EV sales increased by over 500% from 2009-2018, this result suggests that the existence of subsidies explain more than one third of the increase. In the model specification where the number of charging piles is added as an explanatory variable, the subsidy policy coefficient becomes lower yet remains highly significant at the one percent level, as shown in column (4). We note, however, that we only have 411 observations due to the lack of data on charging piles.

[19]The parallel trend means that, in absence of treatment, the difference between the control group and the treated group is constant over time.

Overall, the findings are consistent across all the model specifications presented in the last three columns of Table 3. Control variables such as GDP, gasoline prices and restrictive policies on vehicle ownership led to more private EV purchases, with the price of gasoline exerting the most positive impacts. The number of charging piles also has a positive and significant impact on EV sales, which is consistent with the finding of Ou et al. (2020). We can also see that, when charging piles are accounted for, the impacts of population size and disposable income per-capita become statistically insignificant. We speculate that the reason is that charging piles are more likely to be provided in places with higher population density and/or higher disposable income. Moreover, while the control variables have a statistically significant influence on the treatment effects of the EV subsidy policy, the treatment impacts of this policy remain large and statistically significant.

Table 3: Average Treatment Effect with Full Sample

Variables	(1)	(2)	(3)	(4)
Policy	1.804***	1.795***	1.816***	1.294***
	(13.85)	(13.64)	(14.19)	(5.27)
Population		0.603***	0.583***	0.0179
		(3.33)	(3.31)	(0.16)
Disposable income per-capita		-0.968**	-0.769*	0.839
		(-2.38)	(-1.89)	(0.71)
GDP		0.493**	0.520**	1.594*
		(2.14)	(2.18)	(1.89)
Gasoline price			22.48***	22.51***
			(13.12)	(3.76)
Vehicle restrictive policy			1.342***	0.906***
			(3.74)	(2.79)
Total vehicle holdings			-0.307**	-0.668
			(-2.05)	(-1.48)
Charging piles				0.117**
				(2.06)
Constant	0.0164	2.492	-199.4***	-219.9***
	(0.23)	(0.61)	(-16.08)	(-5.13)
Region fixed effects	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y
Observations	2378	2378	2378	411
R^2	0.915	0.916	0.918	0.938

Note: In parentheses are the robust standard errors. $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01. The same for the following tables.

5.2 Dynamic Marginal Treatment Effects

The estimated results in Table 3 reflect the average influence of the EV subsidy policy on the sales of EVs from 2009 to 2018. Considering that the treatment effects are not static, we

next estimate the dynamics of the relation between EV subsidy policies and EV sales. We do this by running the regression shown in equation 4 to trace out the year-by-year effects. The dynamic results are listed in Table 4. We can see that the incentive subsidy became effective immediately after the implementation of the subsidy policy, and that its positive effect continued to increase in the following years. This finding suggests that the EV subsidy policy became a more important factor in promoting EV sales over time.

Table 4: Dynamic Marginal Treatment Effect with Full Sample

Variables	(1)	(2)
Policy(0)	1.923***	1.873***
	(12.48)	(12.15)
Policy(1)	2.473***	2.396***
	(14.00)	(13.42)
Policy(2)	2.577***	2.464***
	(12.05)	(11.71)
Policy(3)	3.582***	3.439***
	(15.30)	(14.60)
Population		0.420**
		(2.51)
Disposable income per-capita		-0.802**
		(-2.06)
GDP		0.254
		(1.10)
Gasoline price		19.20***
		(10.55)
Vehicle restrictive policy		0.725**
		(2.03)
Total vehicle holdings		-0.171
		(-1.25)
Constant	0.0170	-167.4***
	(0.26)	(-12.19)
Region fixed effects	Y	Y
Time fixed effects	Y	Y
Observations	2378	2378
R^2	0.921	0.922

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

Figure 3 plots the dynamic treatment effects of the subsidy policy on EV sales before and after its implementation. Taking the year of policy implementation as the base time, we show the regression coefficients and 95% confidence intervals for each year. In the X axis, "pre" and "post" present the time before and after the policy implementation, respectively, with the suffix indicating the number of years before or after the base time. Specifically, we consider a ten-year window, spanning from four years before the EV subsidy policy until five years after the implementation of this policy.

As shown in Figure 3, the coefficients on the EV subsidy policy dummy variables fluctuate around 0 with no trends before this policy was implemented. In contrast, the coefficients are significantly different from zero for all years after its implementation, increasing immediately after the EV subsidy policy is introduced in a city. This implies that the treated group and the control group are not significantly different prior to the subsidy policy and thus the parallel trend assumption between these two groups is valid.

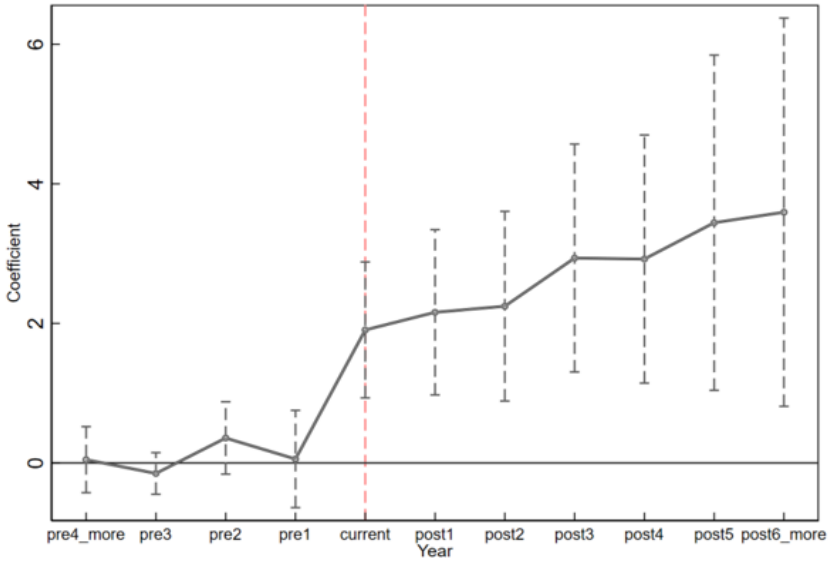


Figure 3: Dynamic Impacts of the EV Subsidy Policy on EV Sales

5.3 Robustness Checks

In this section, we conduct a serious of robustness checks on the above findings. These include applying a different identification strategy, excluding outliers, considering potential endogeneity, conducting placebo tests and running a quantile regression.

5.3.1 Using the PSM-DID approach as identification strategy

A major concern for identifying the effects of EV incentive policies is that the central government might have chosen cities better suited for EV promotion. To address this potential selection concern, we use a PSM-DID strategy. We restrict our attention to the pilot cities and those similar to the pilot cities in terms of socio-economic characteristics, selecting the control group with the PSM method. After ensuring that there are no systematic differences within our samples based on observable characteristics, we then use the DID method to carry out the estimation.

We use the observable information on *population, total vehicle holdings, GDP* and *disposable income per-capita* to construct the covariate vector and estimate the propensity score. With the derived propensity score, we conduct the non-replaceable one-to-one nearest neighbor matching, following Heckman et al. (1997, 1998). The results of the balance test are shown in

Table 5: Balancing Property Test of PSM

Variables	**Matched** or not	**Means** Treated	Control	**Std. Bias (%)**	**Bias red. (%)**	**t value**	**p>|t|**
Population	before	6.213	6.041	26.0		2.33	0.020
	after	6.213	6.265	-7.9	69.6	-0.67	0.502
Vehicle holdings	before	4.061	3.516	69.7		6.23	0.000
	after	4.061	4.064	-0.3	99.5	-0.03	0.978
GDP	before	8.045	7.537	64.9		5.69	0.000
	after	8.045	8.050	-0.6	99.0	-0.05	0.957
Disposable income	before	10.269	10.152	60.6		5.59	0.000
	after	10.269	10.283	-6.7	88.9	-0.44	0.660

Table 5. The results show that the standardized bias of matching covariates is sufficiently small and, thus, the selection of both matching covariates and matching approach is reasonable. In addition, the t-test confirms that there is no systematic difference between the control group and the treated group, implying that the sample used for the empirical analysis is reliable.

The estimates using the PSM-DID method are shown in Table 6. The results are consistent with the findings reported in Table 3, for both average treatment effects and dynamic marginal effects of the subsidy policy. The positive and economically and statistically significant effect of the policy on EV sales was found immediately after its implementation and increases over time.

Table 6: Robustness Check with the PSM-DID Approach

Variables	(1)	(2)
Policy	1.732***	
	(11.58)	
Policy(0)		2.227***
		(11.25)
Policy(1)		2.819***
		(12.62)
Policy(2)		3.212***
		(10.96)
Policy(3)		4.493***
		(13.33)
Control variables	Y	Y
Constant	-198.0***	-130.9***
	(-10.10)	(-6.48)
Region FE	Y	Y
Time FE	Y	Y
Observation	1317	1317
R^2	0.921	0.931

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

5.3.2 Excluding some of the observations

Higher tier cities (e.g., provincial capitals and municipalities) typically have more political clout, and have more resources to administer new programs, and therefore they are more likely to be selected as pilots for the subsidy policy. To deal with this potential endogeneity problem, in this subsection we redo our analysis excluding municipalities and provincial capitals from the sample. The estimation results (see Table7) again confirm the economic and statistical significance of the subsidy to explain the increases in EV sales, and its increased importance over time. In addition, compared with the outcomes shown in Table 3, and controlling for the same independent variables, we can see that the positive impact of the policy is smaller for the cities at relatively lower tiers. We speculate that higher tier cities have greater access to administrative resources, and therefore were better at implementing the subsidy policy. This is consistent with research that established that policies are usually better implemented in provincial cities and municipalities (Li et al., 2016) due to the higher administrative efficiency.

Table 7: Excluding some of the observations

Variables	(1)	(2)
Policy	1.661***	
	(10.77)	
Policy(0)		1.466***
		(8.19)
Policy(1)		2.225***
		(9.78)
Policy(2)		1.771***
		(7.36)
Policy(3)		3.097***
		(10.53)
Control variables	Y	Y
Constant	-204.4***	-195.4***
	(-15.97)	(-13.16)
Region FE	Y	Y
Time FE	Y	Y
Observations	2121	2121
R^2	0.916	0.918

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

5.3.3 Considering the mutual causal relationship

The adoption of policies to subsidize EV sales may depend on consumers' adoption of EVs. That is, more sales may lead the government to introduce more subsidies (as the policy may be considered successful) and more subsidies may lead to more sales. This can give rise to a mutual causality problem. In the same vein, EV sales may also affect the construction of charging piles and the adoption of restrictive policies for vehicle ownership. To address the potential endo-

geneity caused by the mutual causal relationship between dependent and independent variables, we re-run the regression using the one-period lagged value of control variables. We also apply the general method of moments (GMM) that deals with the endogeneity problem by including the lagged dependent variables as the instrumental variables. The estimates are reported in Table 8. They show that our results are remarkably robust; there are only small changes in both average and dynamic marginal effects when considering the endogeneity caused by two-way causality. Therefore, the estimation changes very slightly.

Table 8: Concerning the Mutual Causal Relationship

Variables	**Control Variable Lagged**		**GMM**
	(1)	(2)	(3)
Policy	1.526***		2.343***
	(12.66)		(3.40)
Policy(0)		1.544***	
		(10.21)	
Policy(1)		2.030***	
		(11.25)	
Policy(2)		1.826***	
		(8.63)	
Policy(3)		2.740***	
		(11.43)	
Control			Y
L.Control	Y	Y	
Constant	-395.1***	-355.6***	
	(-15.25)	(-12.17)	
Region FE	Y	Y	Y
Time FE	Y	Y	Y
Instruments			23
AR(1)			0.972
AR(2)			0.921
Sargant test(p)			0.281
p-value			0.00
Observations	2046	2046	1478
R^2	0.930	0.932	

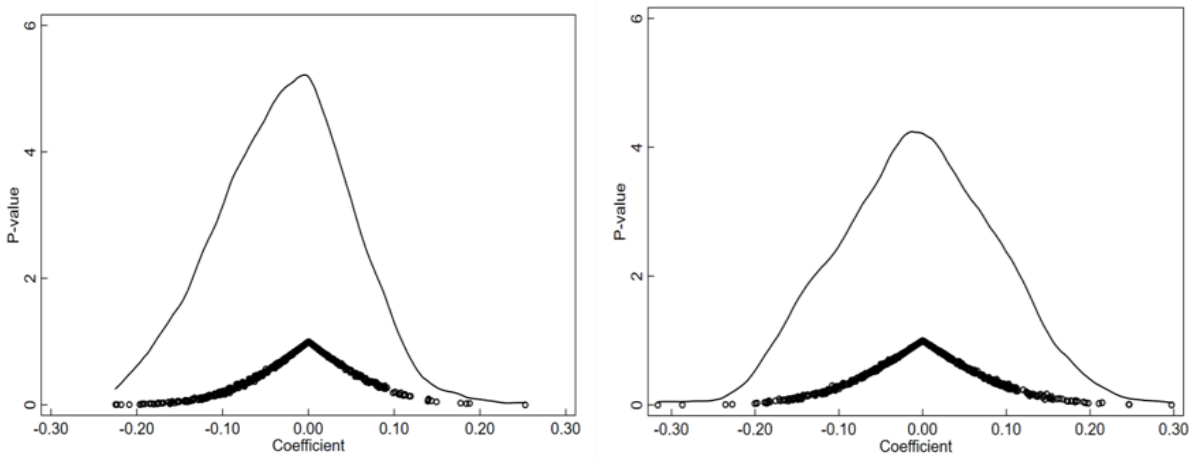
Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

5.3.4 Placebo tests

In addition to the EV subsidy policy, there may be other ways to promote EV sales. Therefore, it is necessary to conduct placebo tests to check whether our main findings were induced by other unobservable factors. We do this by carrying out two counterfactual tests. In the first test, we randomly set the adoption time of the EV subsidy policy in each city. In the second test, we randomly assign the cities as treated samples, following Chetty et al. (2009) and Cai

et al. (2016). In both placebo tests, we repeat the benchmark regression 500 instances to obtain the probability distribution of the coefficient estimates.

The results are shown in Figure 4, where the X axis depicts the estimated policy coefficients obtained from the 500 times of regression. Figure 4 (a, b) show the kernel density distribution of these coefficients and the dots at the bottom are corresponding p values. The mean of these estimates is around zero and most of the estimates fall between -0.3 and 0.3, indicating that only a very limited number of estimates fall right of 1.294 (i.e., the coefficient in the last column of Table 3).[20] We can then conclude that our estimates are not severely biased due to any omitted variables.



(a) Randomly Changed Policy Adoption Time (b) Randomly Assigned Pilot Places

Figure 4: Placebo Tests

5.3.5 Quantile regression

The regression methods we have applied by far only estimate the conditional mean of EV sales across the values of the independent variables. To avoid the impacts from outliers, in the following we will employ a quantile regression to estimate the EV subsidy policy's treatment effect on several quantiles of EV sales. The estimates obtained with 25%, 50%, 75% and 90% quantiles of China's EV sales are reported in Table 9.

The estimates in Table 9 imply that the subsidy policy has a larger impact for the 25% and the 90% quantile of EV sales in China, revealing that the subsidy policy works better at the beginning of market expansion and at the time when the market slackens due to the higher penetration of EVs. Overall, the positive effect of the policy is found across all quantiles examined, consistent with the findings from the benchmark regression. Moreover, the dynamic treatment effects are also in line with the main findings, as shown in Table 13 in Appendix A, further verifying the robustness of the conclusions.

[20]To help with visualization, the values above 0.3 are not shown on the X axis, as most estimates fall in the narrow interval between -0.3 and 0.3.

Table 9: Robustness Check with Quantile Regression

Variables	Q25	Q50	Q75	Q90
	(1)	(2)	(3)	(4)
Policy	3.188***	2.897***	2.867***	3.324***
	(11.58)	(6.19)	(13.85)	
Control	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	2380	2380	2380	2380

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

6 The Heterogeneous Impact of Subsidies on EV Sales

The results from the previous section provide strong evidence that the subsidy policy on EV has had an economically and statistically significant impact on EV sales across China. In this section, we explore the impact of the subsidy policy by type of EV and across cities and regions.

6.1 Heterogeneity of EV type

China's EV subsidy policies cover four types of EVs, namely, battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV), extended-range electric vehicles (EREV) and fuel cell electric vehicles (FCEV). There are very few sales of FCEVs in China due to the immature nature of technology and limited production capacity. Thus, we will focus on the impact of the subsidy policy on the sales of BEVs, CEVs and HEVs only.

The results are reported in Table 10, and show that the subsidy policy plays a significant role in promoting the sales of all three types of EVs, and that the impact increases over time, While the individual coefficients are different, these results are in line with those found with the full sample. In addition, the treatment effect on BEV sales is far larger than that on the sales of PHEVs and EREVs, and the positive effect on PHEV sales is slightly larger than that on EREV sales, reflecting China's EV development strategy that prioritizes BEVs.

6.2 Heterogeneity of City Size

Chinese cities are vastly different in terms of infrastructure, human resources, business opportunities, administrative resources at the city level and consumer sophistication, Hence, this subsection explores how the impact of the subsidy policy on EV sales varies across cities. For this purpose, we divide cities into four groups: tier-1 cities (i.e., Beijing, Shanghai, Guangzhou and Shenzhen, which are the four largest cities in China); tier-2 cities (e.g., Chengdu and Wuhan); tier-3 cities (e.g., Wenzhou and Yantai); and a fourth group comprising the remaining cities considered in this study.[21] We re-run the regression, with the estimates shown in

[21] For classification of cities, we refer to the tier system of China's cities at Baidu.

Table 10: Heterogeneity of EV Type

Variables	BEV		PHEV		EREV	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	2.543***		0.399**		0.332***	
	(12.24)		(2.08)		(4.41)	
Policy(0)		3.321***		0.725		0.508***
		(10.27)		(1.41)		(5.04)
Policy(1)		4.135***		1.296***		0.358***
		(12.47)		(2.71)		(3.10)
Policy(2)		4.471***		1.649**		0.705***
		(9.10)		(2.16)		(4.46)
Policy(3)		6.217***		2.209**		0.703***
		(11.35)		(2.45)		(4.21)
Constant	-553.7***	-319.7***	-1.850**	-2.533***	-214.3***	-185.4***
	(-5.51)	(-3.07)	(-2.52)	(-5.06)	(-14.68)	(-11.40)
Controls	Y	Y	N	N	Y	Y
Region FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Obs.	975	975	568	568	1811	1811
R^2	0.835	0.849	0.923	0.924	0.924	0.926

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

Table 11.

As Table 11 shows, the treatment effect of the subsidy policy is economically and statistically significant across all city groups, and this is consistent with the main findings reported in Section 5. In addition, the coefficients for the first- and fourth-tier cities are relatively larger. The larger treatment impact for the largest cities may be a result of a greater ability to implement policy in these cities, as discussed in subsection 5.3.2. It may also be related to consumers in larger cities having higher purchasing power and greater awareness of environmental issues. We conjecture that the large impact of the policy found for the smaller cities in the fourth group is simply a reflection of the number of EV sales being low, implying a high marginal impact. The dynamic effects of the subsidy policy on EV sales by city tier are shown in Table 14, in Appendix B.

The marginal effects are positive, and economically and statistically significant, for all cities after the policy implementation, except for the first two years in the largest cities. The largest cities were the first to pilot the subsidy policy, and consumer awareness may have been low at the time. The policy was later extended to smaller cities, and by that time EVs may already have become more popular. As shown by Ye et al. (2021), based on a sample of over 1,000 consumers across China, consumers' international intention to buy are affected by the interaction of psychological factors, such as attitudes, and economic factors, such as the existence of subsidies.

Table 11: Heterogeneity of City Size

Variables	First-tier	Second-tier	Third-tier	Fourth-tier
	(1)	(2)	(3)	(4)
Policy	1.493***	1.391***	1.346***	1.621***
	(3.13)	(5.36)	(4.75)	(7.37)
Control	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	155	248	596	1379
R^2	0.946	0.948	0.916	0.923

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

6.3 Heterogeneity of Region

Geographic location is an important driver of the performance of firms and consumer behavior. Natural resources endowment, economic and technological development level, social and cultural norms, and the enforcement of policies can vary considerably across different regions. In this subsection, we investigate the impact of the subsidy policy on EV sales across three regions (East, Central, and West). To do so, we separated the 286 cities in our sample into the three regions.

Table 12: Heterogeneity of Region

Variables	East		Central		West	
	(1)	(2)	(3)	(4)	(5)	(6)
Policy	1.261***		2.291***		2.144***	
	(7.97)		(9.63)		(5.90)	
Policy(0)		1.273***		2.151***		1.998***
		(6.33)		(7.24)		(4.62)
Policy(1)		1.435***		3.038***		2.988***
		(6.39)		(10.51)		(5.73)
Policy(2)		1.503***		2.637***		2.571***
		(5.57)		(6.48)		(4.60)
Policy(3)		1.927***		3.826***		4.664***
		(6.07)		(10.05)		(7.20)
Policy(4)		2.038***		3.398***		2.945***
		(5.59)		(7.74)		(3.41)
Controls	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Obs.	849	849	820	820	709	709
R^2	0.937	0.938	0.924	0.928	0.907	0.914

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

As shown in Table 12, the average treatment effects are positive, and economically and

statistically significant, across all regions, with the impact in the eastern region being the lowest and that in the central region being the highest. There are several reasons that may explain this difference, including differences in disposable income, and the availability of infrastructure such as charging piles. The dynamic marginal effects suggest that the impact of the subsidy policy on EV sales has exhibited different patterns across the three regions.

7 Concluding Remarks

Based on panel data covering 286 prefecture-level cities in China from 2009 to 2018, this paper estimates the impact of the introduction of subsidies on EV private sales. Our econometric approach, DID, allows us to construct a natural experiment where the treated group are the cities where subsidies comprises introduced, and the control group comprises the cities where subsidies were not available. We have successful dealt with the potential endogeneity that may have arisen from any bias in the selection of cities where subsidies were introduced, and we were able to explore the dynamic nature of the data.

The benchmark results provide evidence that the subsidy policy has had a significant impact on EV sales in China. We estimate an average annual increase in EV sales from 2009 to 2018 of 120%. This represents around one quarter of the actual increase in sales. In addition, the analysis on dynamic marginal treatment effects shows that the impact of the policy is sustained over time; the yearly impact of the subsidy policy on private EV increases after the implementation of policy. Moreover, control variables, such as the number of charging plies, also influence the sale of EVs. These findings are robust across model specifications. They are also remarkably robust across identification and empirical strategies, including applying a different identification strategy, excluding outliers of observations, concerning potential endogeneity, conducting placebo tests and running quantile regressions.

The positive impact of the subsidy policy on EV sales, both on a yearly basis and over time after its implementation, is also found when the analysis is undertaken across EV types, city sizes and regions. In particular, the presence of subsidies has a greater impact on the sales of BEVs than on other types of EVs, on the sales of EVs in relatively larger and smaller cities than in medium-size cities, and on sales in the central and western cities more than the eastern cities.

The results provide clear, robust evidence that subsidies are an important factor that explains the growth in EV sales. This is a significant conclusion as the Chinese government has spent over 208.7 billion RMB on subsides since 2009.[22] While our results do not imply that the subsidies, as a public policy, are more effective than say providing infrastructure or other policy initiatives, they do provide a high degree of confidence that subsidies work as intended, and their impact is sustained over time. The impact of the subsidies, and their sustainability over time, however, vary across EV types, city types and regions. This suggests that the choice

[22]This number is for new energy vehicles (including EVs, plug-in hybrid vehicles, fuel cell-powered vehicles and hybrids), but the subsidy for other new energy vehicles accounts for only a very small fraction. See `http://m.evpartner.com/news/detail-34020.html` and `https://www.sohu.com/a/438330981_679112`.

of the optimal policy mix (e.g., subsidies, infrastructure, restrictions on conventional vehicles, non-price incentives) will depend on local/regional characteristics.

This paper also raises several questions that deserve further investigation. For example, it is unclear why the impact of subsidies increases over time. This may be due, for example, to greater consumer awareness. If so, then subsidies may be less needed in the future. In a similar vein, while the higher impact of the lowest quantile of sales may simply be a function of the small number of sales (implying a higher marginal impact), it is less clear why the impact is also higher for the highest quantile of sales.

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Appendices

Appendix A: Dynamic Treatment Effects of Quantile Regression

Table 13: Dynamic Treatment Effects of Quantile Regression

Variables	Q25	Q50	Q75	Q90
Policy(0)	2.640***	2.990***	2.902***	2.959***
	(176.89)	(253.77)	(106.98)	(72.93)
Policy(1)	2.960***	2.933***	2.949***	3.127***
	(27.26)	(480.98)	(80.15)	(177.40)
Policy(2)	3.947***	3.645***	3.218***	3.216***
	(107.26)	(151.34)	(58.86)	(74.33)
Policy(3)	4.421***	4.122***	3.955***	3.978***
	(33.01)	(178.30)	(58.09)	(32.22)
Control	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	2380	2380	2380	2380

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.

Appendix B: Heterogeneity Analysis in City Sizes – Dynamic Treatment Effects

Table 14: Heterogeneity Analysis in City Sizes – Dynamic Treatment Effects

Variables	First-tier	Second-tier	Third-tier	Fourth-tier
	(1)	(2)	(3)	(4)
Policy(0)	0.822	1.237***	1.089***	1.384***
	(1.51)	(3.50)	(4.04)	(4.51)
Policy(1)	1.580	1.444***	2.231***	1.607***
	(1.63)	(3.99)	(7.04)	(3.58)
Policy(2)	1.934***	1.106**	1.050***	1.843***
	(2.73)	(2.56)	(2.73)	(4.28)
Policy(3)	2.315***	1.404***	2.630***	2.177***
	(2.95)	(3.34)	(6.11)	(4.28)
Control	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	155	248	596	1379
R^2	0.951	0.948	0.926	0.917

Note: $*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01.