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Effectiveness of electric vehicle subsidies in China: A three-dimensional panel study

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Effectiveness of electric vehicle subsidies in China:

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Abstract: Electric vehicles (EVs) are likely to emerge as the main means of zero-emission road transport. China has used a variety of policy approaches to encourage EV adoption, including vehicle purchase subsidies. This study uses a three-dimensional dataset to estimate the effect of purchase subsidies for domestic EVs on adoption in 316 cities in China over January 2016–December 2019. An instrumental variable approach that utilizes the timing of the cancellation of local subsidies by the central government is pursued. The findings suggest that purchase subsidies for domestic EVs have led to a sizeable increase in uptake, but have discouraged uptake of imported EVs. Higher consumer awareness of the subsidies is associated with a larger proportional effect on uptake of domestically-produced vehicles. We estimate that increases in the per-vehicle subsidy rate have on average reduced carbon dioxide (CO_2) emissions at a marginal subsidy cost of about 4,453 CNY (US$712) per tonne, which is high. However, other benefits, including long-run benefits from the emergence of a new clean technology sector, may be substantial.

Keywords: electric vehicle subsidies; consumer awareness; imported vehicles; carbon dioxide emissions

JEL codes: H23, H31, Q58

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1. Introduction

Road transportation is a major contributor to climate change and energy security challenges, accounting for about 10% of China's greenhouse gas emissions (Ministry of Ecology and Environment of China 2020) and 43% of China's oil consumption in 2019 (International Energy Agency (IEA) 2021). To accelerate the switch to electrified road transport, China has introduced a range of incentives to promote battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell electric vehicles (FCEVs).[1] The principal incentive mechanism has been purchase subsidies for domestically-produced EVs applied at both the national and local levels.

Subsidies are used in many countries to encourage deployment of EVs and other clean technologies such as solar panels. A key motivation is that, in the absence of an appropriate carbon price, the social benefit of EV adoption is likely to exceed the private benefit, assuming an internal combustion engine vehicle would have been purchased instead (Lin and Tan 2017; Rapson and Muehlegger 2023). In a large economy such as China, purchase subsidies for domestically-produced vehicles should be expected to encourage domestic production, helping firms and the industry to achieve economies of scale.

In China, EVs have been sold at a price equal to the retail price reduced by the per-vehicle purchase subsidy amount, with the seller then receiving any subsidy payments from the central and local governments. The relevant pre-subsidy retail price may well have been lower in the absence of the scheme. In effect, China's EV subsidies should thus be expected to have both lowered the price paid by consumers and increased the price received by sellers; the final incidence is likely to have been shared.

China is the largest EV market in the world and accounted for about half of the global electric car stock as of 2021 (IEA 2022). While central EV purchase subsidies for urban passenger electric vehicles were cancelled at the end of 2022, China's government still plans to use purchase subsidies to spur the adoption of hydrogen FCEVs, intelligent networked EVs, and EVs in rural areas (Ministry of Transport of China 2022; National Energy Administration of China 2022). Some cities also reintroduced purchase subsidies in 2023.

[1] BEVs are automobiles that run purely on electricity and do not use fuel. PHEVs are automobiles that use electricity but also have an internal combustion engine. FCEVs are automobiles that use energy stored as hydrogen and convert this to electricity using fuel cell technology.

This study uses the substantial variation in purchase subsidy rates by electric driving range, city, and month in China to estimate the effect of purchase subsidies on the adoption of EVs. Monthly data on new EV registrations, purchase subsidies, and other incentives were compiled for 316 cities and 8 range classes for the period January 2016–December 2019. The study covers all cities in mainland China outside the Xinjiang and Tibet Autonomous Regions, accounting for almost 99% of mainland China's total EV registrations over the study period.

We collected data on vehicle registrations and various EV incentive policies in each city to answer two questions. First, how large has the effect of EV purchase subsidies been on EV adoption? Second, what is the subsidy cost of reducing CO_2 emissions via this mechanism? Early evidence from the US and Canada suggested that subsidizing EVs has to date been a relatively expensive approach for reducing CO_2 emissions (Azarafshar and Vermeulen 2020; Xing et al. 2021; Sheldon 2022). The required subsidy to reduce CO_2 emissions via this mechanism in China, the world's largest greenhouse gas emitter, is not yet known. As the largest subsidy program for what is a key technology for the energy transition, the topic is of substantial public policy interest. Our results are potentially relevant for informing policies to accelerate EV uptake in other countries and the uptake of other clean technologies.

We initially estimate fixed-effect linear regression (LR) and negative binomial (NB) specifications using a three-dimensional dataset, with both the dependent variable (new domestically-produced EV registrations) and the key explanatory variable (the per-vehicle purchase subsidy) varying by electric driving range class, city, and month. We then use an instrumental variable (IV) approach that exploits the fact that China's central government decided to remove all purchase subsidies for domestically-produce EVs as of mid-2019, a situation that lasted until the end of our dataset. We also estimate the effects of the EV purchase subsidies on new registrations of imported EVs and on total registrations of EVs (domestic plus imported). purchase subsidies for domestic EVs

The results indicate that higher purchase subsidies for domestically-produced EVs tend to increase registrations of domestically-produced EVs and discourage the uptake of imported EVs. Of particular interest is that the proportional effect of purchase subsidies is larger where awareness of subsidies is higher and in less-developed cities. We also find that it increased over time. Results of a simulation suggest that, as of 2019, a 1,000 CNY increase in the per-vehicle purchase subsidy rate would have led to a reduction of more than 275,287 tons of lifetime-of-use CO_2 emissions from additional sales of EVs in China. The subsidy cost of eliminating one tonne of CO_2 via this mechanism is calculated to have been about 4,453 CNY (US$712).

This is the first study to instrument the per-vehicle purchase subsidy to address potential endogeneity issues. It is also the first to compare the effects of China's purchase subsidies for domestically-produced EVs on registrations of both domestically-produced and imported EVs and to investigate the cost effectiveness of EV purchase subsidies in reducing CO_2 emissions in China. An additional contribution is using measures of consumer awareness of EV purchase subsidies based on information scraped from an online discussion forum to explore the importance of knowledge on EV subsidies for subsidy effectiveness.

The remainder of the paper is structured as follows. Section 2 presents the literature review and details about China's EV incentive policies. Section 3 describes the data. Section 4 presents our methods. The results are presented in section 5. Section 6 presents a calculation of the cost effectiveness of reducing CO_2 emissions via an increase in the purchase subsidy rate. Section 7 concludes.

2. Background

2.1 Literature review and our contribution

A number of prior studies have investigated the effectiveness of EV incentives in developed countries. These have generally found a sizeable positive effect on uptake (Beresteanu and Li 2011; Gallagher and Muehlegger 2011; Jenn et al. 2013; 2018; Azarafshar and Vermeulen 2020; Xing et al. 2021), including from both financial and non-financial incentives (Hardman 2019; Kumar and Alok 2020). However, in some instances EV purchase subsidies have been found to not be highly cost-effective in delivering environmental benefits or reducing CO_2 emissions (Azarafshar and Vermeulen 2020; Sheldon 2022; Sheldon et al. 2023). Coffman et al. (2017) reviewed the literature on factors affecting EV adoption and found that, despite notable progress, key government goals for adoption in developed countries were not always met.

Several studies have focused on China, analyzing either sales data (Ma et al. 2017; Wang et al. 2017a; Qiu et al. 2019; Kalthaus and Sun, 2021; Li et al. 2022; Yao et al. 2022; Zheng et al. 2022) or consumer surveys (Zhou et al. 2015; Wang et al. 2017b; Lin and Wu 2018; Qian et al. 2019; Sheldon and Dua 2020; Wang et al. 2020; Lu et al. 2022). Subsidies have been concluded to be the major contributor to the increase in China's EV sales, especially for BEVs (Zheng et al. 2022). They have imposed a sizeable financial burden on the government, however (Wang et al. 2022a). While there are estimates of the effect of the existence of EV purchase subsidies using a dummy variable approach, detailed estimates of the effect of the per-vehicle subsidy rate are yet to be presented (Zheng et al. 2022). The cost effectiveness of the subsidy scheme also remains unclear.

Some scholars have made the case that other incentive policies, such as support for the construction of charging facilities and research and development subsidies, may be a better option in the future than continued use of broadscale purchase subsidies (Wang et al. 2022a; Zheng et al. 2022; Li et al. 2023). However it has also been argued that there is an ongoing role for subsidies to be used to address short-term pressures on EV sales such as at times of negative shocks (Liu et al. 2023).

The studies of Jenn et al. (2018) and Azarafshar and Vermeulen (2020) used model-level EV data for the US and Canada respectively. For China, we instead aggregate the raw vehicle model-level data to the range class level given that the degree of persistence of EV models in the dataset is low – individual models come and go. Specifically, the number of EV models in our sample increased from 63 in 2016 to 348 in 2019, with an average number of available months per model of only 8. According to the IEA (2022), there were close to 400 EV models available in China in 2021, compared to only 70 in the US. Using range class level data allows us to analyze a period of 48 months and better facilitates the use of approaches such as distributed lag estimations. The treatment variable – the per-vehicle purchase subsidy – is also one that has been set at the vehicle range level by the central and local governments.

Most studies for China have used two-dimensional city-time data. Li et al. (2022) used a three-dimensional dataset, however their sample covered less than half the number of cities in our dataset. The current paper uses the largest (316 cities) and newest (as of 2019) dataset on per-vehicle subsidies and EV adoption in China to date, with the number of observations in our sample exceeding 120,000. One of the advantages of a three-dimensional dataset is that at the two-dimensional city-month level there may be reverse causality from vehicle purchase numbers to the average purchase subsidy rate, as there are different subsidy rates for vehicles with different electric ranges in each city and month. Our three-dimensional estimations avoid this issue, as the electric range definitions that we use are those used to determine the per-vehicle subsidy rates under the subsidy scheme.

We pay careful attention to accurate measurement of the relevant per-vehicle subsidy on a monthly basis. The month when a new policy was implemented is used in variable construction. We also use temporary subsidy rates during transition periods. In contrast, key prior studies such as the study of Kalthaus and Sun (2021) have used constant subsidy rates for a whole year, which loses some of the temporal dynamics. Our main specification uses the average per-vehicle subsidy in each range class rather than the ceiling per-vehicle purchase subsidy in a city as used in previous studies such as that of Ma et al. (2017).

A number of prior studies, such as those of Ma et al. (2017), Wang et al. (2017a), Qiu et al. (2019), and Kalthaus and Sun (2021), focused on the early stage of China's EV adoption journey prior to 2016 – when purchase subsidies and many other incentives were limited to only pilot cities. We use a more up-to-date sample period that covers the key years of China's purchase subsidies.

It is useful to have a dataset that extends to 2019 in order to incorporate two key changes. First, the abrupt cancellation of all local EV subsidies in July 2019 provides a source of variation in vehicle subsidies that we use to help identify their effects. Second, in 2019 China also commenced a "dual credit" policy involving both the Measures for Passenger Cars Corporate Average Fuel Consumption and the New Energy Vehicle Credits Regulation. If the fuel consumption of conventional vehicles is higher than the corresponding fuel consumption standard, the producer receives negative credits. Otherwise, positive credits are earned. Production of EVs is also rewarded with positive credits, and carmakers face penalties if their total number of credits does not meet the target set by the government. This policy was enacted to promote the development and commercialization of EVs as China moves toward a post-subsidy period (He et al. 2020). We control for these credits on a per-vehicle basis in our estimations.

A key methodological innovation of our study is the approaches used to address potential endogeneity challenges. This is important as there may be third factors that influence both per-vehicle subsidy rates and the number of new EV registrations, such as local preferences. There is yet to be a study that uses an IV approach to address the endogeneity concern about subsidy rates or that covers a comprehensive sample of Chinese cities and EV models. Although for example the study of Jenn et al. (2018) considered the potential endogeneity issue, the context of China differs from North America in that China's per vehicle subsidies have been a direct function of the electric driving range, which could exacerbate the endogeneity challenge in the absence of a credible identification strategy.

Although imported EV models can enjoy some incentives in China, such as driving restriction exemptions and toll exemptions, a characterizing feature of China's EV purchase subsidy schemes is that only domestic or joint-venture EVs have been eligible; imported EVs have been excluded. Our detailed dataset allows us to estimate separate effects for both imported EVs and domestically-produced EVs for the first time. We construct a four-dimensional dataset to conduct the comparison, consisting of separate data for domestically-produced and imported EVs and arranged by range class, city, and month.

An additional contribution of the current study is that we examine the effect of consumer awareness in China on the impact of purchase subsidies. In a prior study of the US, Jenn et al. (2018) used readership of newspaper articles to reflect knowledge of EV incentives in the US. We instead use data on consumer awareness obtained by scraping information from China's largest vehicle discussion forum, presenting specifications in which we interact these measures with the per-vehicle purchase subsidy variable.

Ours is the first study to investigate the effectiveness of EV purchase subsidies in reducing CO_2 emissions in China. The findings suggest that China's purchase subsidy scheme for EVs has to date been an expensive approach for reducing CO_2 emissions. However, the broader implications of the subsidy scheme in terms of reducing air pollutants and nurturing this new clean technology are also important to consider.

2.2 China's incentive policies for EVs

China's incentives for EVs are usually categorized into supply-side and demand-side policies (Qiu et al. 2019). Supply-side policies focus on EV manufacturers and include model development prizes, manufacturing prizes, and monetary rewards for achieving a certain quantity of sales. Demand-side policies focus on consumers and include purchase subsidies, purchase tax exemptions, and exemptions from purchase restrictions. EV drivers in China have also been exempted from driving restrictions, the vehicle and vessel (V&V) tax, parking fees, bridge and road tolls, compulsory insurance fees, and public charging fees. They have also benefitted from preferential access to bus lanes (Wang et al. 2019).

There are two kinds of EV purchase subsidy in China. First, a subsidy from China's central government that commenced in 2016 and has varied by electric driving range class. Per-vehicle purchase subsidies from the central government were reduced by 20% over 2017–2018 and by 40% by 2019 relative to the 2016 level (Ministry of Finance (MOF) of China 2015). It was planned that the central government subsidies would be completely eliminated in 2020. However, in 2019 EV sales fell for the first time (see Figure 1) – perhaps at least in part due to the reduction in purchase subsidies (Wang et al. 2019; IEA 2020a). In early 2020, COVID-19 then posed challenges for China's auto industry (Ouyang et al. 2021). To stimulate demand, China's government decided that instead of eliminating purchase subsidies, per-vehicle subsidies for EVs would be cut by only 10%, 20%, and 30% year-on-year in 2020, 2021, and 2022 respectively. They were cancelled at the end of 2022 (MOF of China 2020).

Table 1 summarizes the central per-vehicle purchase subsidy over 2016–2019. In 2016 and 2017, the threshold electric driving range to qualify for the subsidy for BEVs was 100 km, and there were three increments. In 2018, the threshold range to qualify for the subsidy for BEVs increased to 150 km and the number of increments increased to five, with March–June 2018 as the transition period. The threshold range for BEVs increased to 250 km in 2019, with April–June 2019 as the transition period. The threshold range to qualify for a PHEV purchase subsidy was 50 km throughout. In 2020, a new regulation on the purchase subsidy program came into effect that meant that the pre-subsidy retail price of EVs could no longer exceed 300,000 CNY (US$48,000) (MOF of China 2020).

The second kind of EV purchase subsidy has been provided by local governments at the provincial or city levels, with the subsidy rate varying by range class, city, and month. Local governments set their subsidies as a proportion of the central per-vehicle subsidy, with this proportion declining over time during our sample period. Typically, large cities implemented local subsidies earlier and at a higher per-vehicle rate than others, although there is variation even among cities of similar size. All local purchase subsidies in China were cancelled as of June 2019 (MOF of China 2019), with only the national purchase subsidies remaining until the end of our sample period.

Table 1 EV purchase subsidy per vehicle (CNY) from China's central government, 2016–2019

Announcement date	Applicable period	BEVs						PHEVs
		R<100km	100km≤R<150km	150km≤R<250km	R≥250km			R≥50km
22 May 2015	1.2016–12.2016	0	25,000	45,000	55,000			30,000
29 December 2016	1.2017–2.2018	0	20,000	36,000	44,000			24,000
12 February 2018	3.2018–6.2018	0	14,000	25,200	30,800			16,800
		R<100km	150km≤R<200km	200km≤R<250km	250km≤R<300km	300km≤R<400km	R≥400km	R≥50km
26 March 2019	7.2018–3.2019	0	15,000	24,000	34,000	45,000	50,000	22,000
	4.2019–6.2019	0	1,500	2,400	20,400	27,000	30,000	13,200
	7.2019–12.2019	0	0	0	18,000	18,000	25,000	10,000

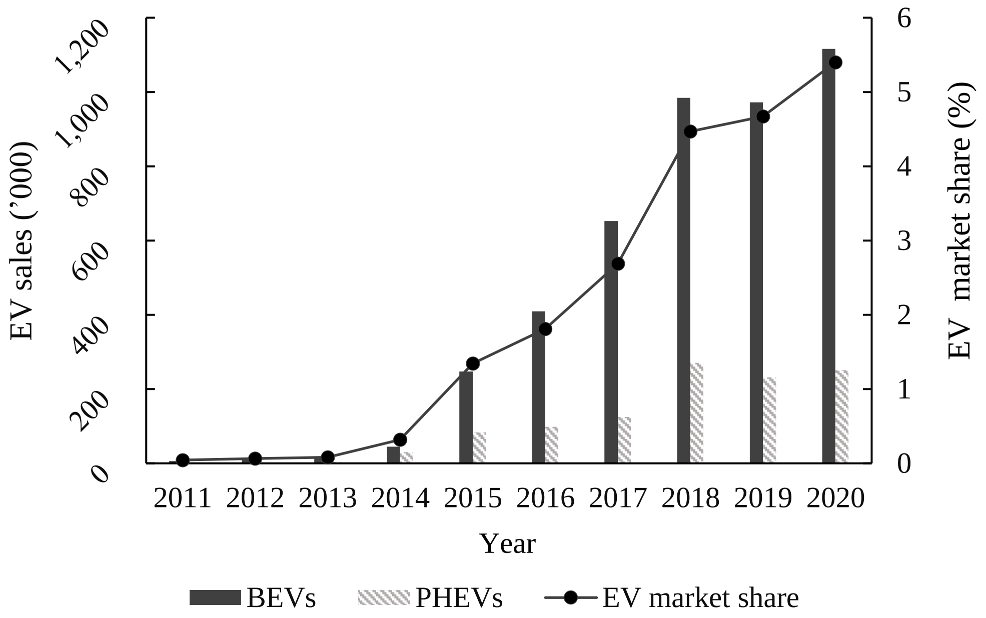
Notes: *R* represents the electric driving range in km. Electric driving range refers to the distance a vehicle can travel on battery power alone based on a single charge. FCEVs are omitted. Values in this table are not deflated. March–June 2018 and April–June 2019 were transition periods with temporary subsidy rates.

3. Data

3.1 EV registrations

China has seen rapid EV uptake. As shown in Figure 1, EV sales surged in 2015, with the EV share of auto sales passing 1%. Since 2017, China has accounted for more than half of all EV sales globally (IEA 2018). Strong growth has been witnessed in sales of BEVs in particular, with annual BEV sales passing one million in 2020. This has likely in part been aided by BEV-favouring policies (Huang and Qian 2018; Hao et al. 2020) – for example, purchase subsidies from the Beijing local government have been offered for BEVs but not PHEVs. FCEV sales volumes remained low in 2020, at only about 1,000 – mostly buses, trucks, and vans (China Association of Automobile Manufacturers (CAAM) 2021). FCEV technology is still relatively underdeveloped and expensive, and hydrogen refuelling stations remain uncommon in China.

Figure 1 Annual sales of EVs in China, 2011–2020



Source: CAAM (2021). *Notes*: EVs are cars only in this figure – both passenger cars and commercial cars. EV market share is as a % of total car sales. FCEV sales are not shown.

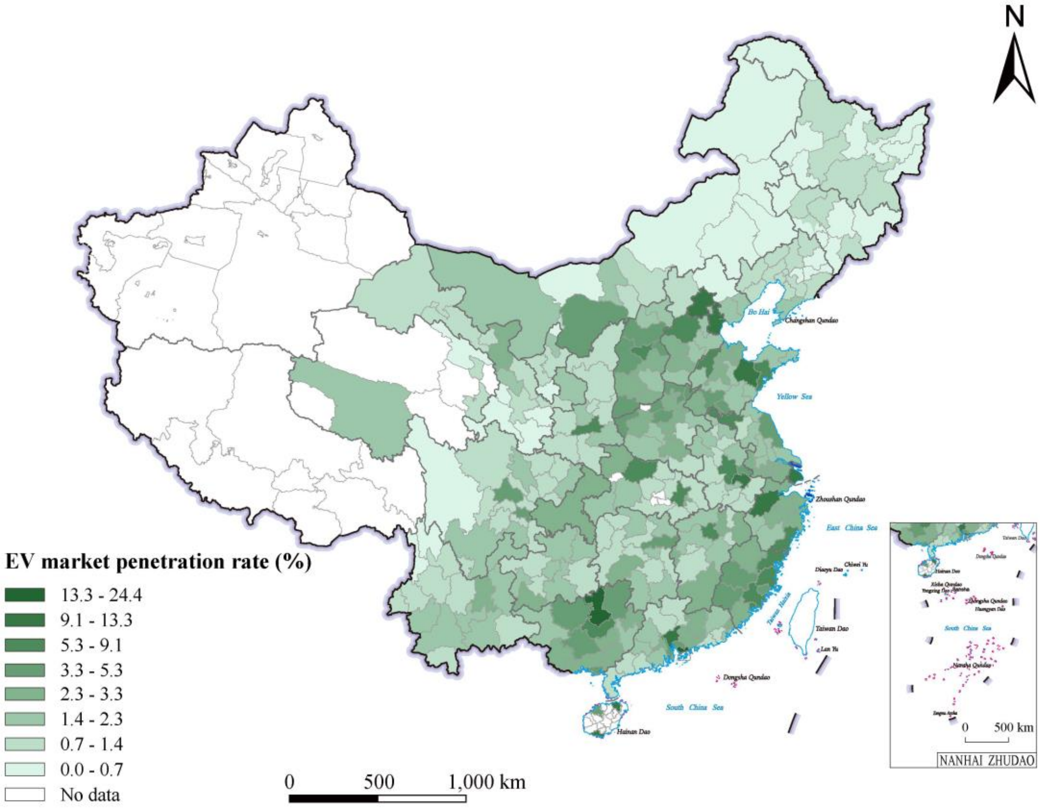
We use new EV registration data for a comprehensive sample of cities in China over the period January 2016–December 2019. The data were obtained from Huaguanyun automobile big data platform and include the number of new registrations in each city in each month as well as the brand, manufacturer, vehicle model, vehicle type (car, crossover, multi-purpose vehicle, or sport utility vehicle), fuel type (BEV, PHEV, or FCEV), whether a vehicle is produced domestically or imported, and whether a vehicle is purchased by an individual or an institutional buyer such as a government agency. The data do not cover heavy-duty vehicles such as buses. We exclude months prior to 2016 because the market was nascent at that time, with the number of new EV registrations typically being zero in many cities. FCEVs are not included in the study given their low take-up. Our dataset ends before the lockdowns related to COVID-19 in early 2020.

We constructed a three-dimensional dataset of new EV registrations, with data arranged by electric driving range, city, and month. Electric driving range refers to the distance a vehicle can travel on a single battery charge. The dataset includes 348 vehicle models and is categorized into 8 classes according to electric driving range: seven groups for BEVs (range<100km, 100km≤range<150km, 150km≤range<200km, 200km≤range<250km, 250km≤range<300km, 300km≤range<400km, range≥400km), and one for PHEVs.[2] The grouping follows the subsidy tiers set by the central government as described in section 2.2. All EVs in the same range class enjoy the same subsidy from the central government at any time. We collected each vehicle model's electric driving range from Autohome New Energy Vehicle (NEV), one of the largest NEV websites in China.[3] The panel is at the city rather than province level because cities in the same province have provided different incentives.

We collected separate balanced panel data for registrations of both domestically-produced and imported EVs. Each covers 316 cities in mainland China. This includes four direct-administered municipalities (i.e. Beijing, Shanghai, Tianjin, and Chongqing) and all prefecture-level cities other than those in the Xinjiang and Tibet Autonomous Regions. Cities that had their prefecture-level city status revoked (such as Laiwu in Shandong province) during 2016–2019 are not included. Registrations of EVs include those registered by both urban and rural residents. Figure 2 shows the share of new EV registrations in the total number of new passenger vehicle registrations by city in 2019. Developed cities in the east of the country tend to have a higher EV penetration rate.

[2] We do not categorize PHEVs by range as the central subsidy was the same for most PHEV ranges.
[3] https://ev.autohome.com.cn.

Figure 2 EV market penetration rate by city, 2019



Notes: Shows the ratio of new EV registrations to all new passenger car registrations, expressed as a percentage. EVs include both domestically-produced and imported. The definition of a city refers to the administrative division and includes rural and hinterland areas in the vicinity.

3.2 EV purchase subsidies

We referred to local provincial and city government websites and EVpartner, a source that collects all city-level policy documents on promoting EVs in China, to determine whether an incentive policy, including a local purchase subsidy, was in place in a city during a month.[4] We focus primarily on demand-side policies, as supply-side policies should have mostly similar effects across cities given that vehicles can be sold across the country.

The per-vehicle purchase subsidy measure used in our regressions represents the central plus local per-vehicle purchase subsidies averaged across all new registrations of EVs in the driving class range, city, and month. The consumer price index (CPI) for China was then used to adjust to a 2016 base. The data vary by:

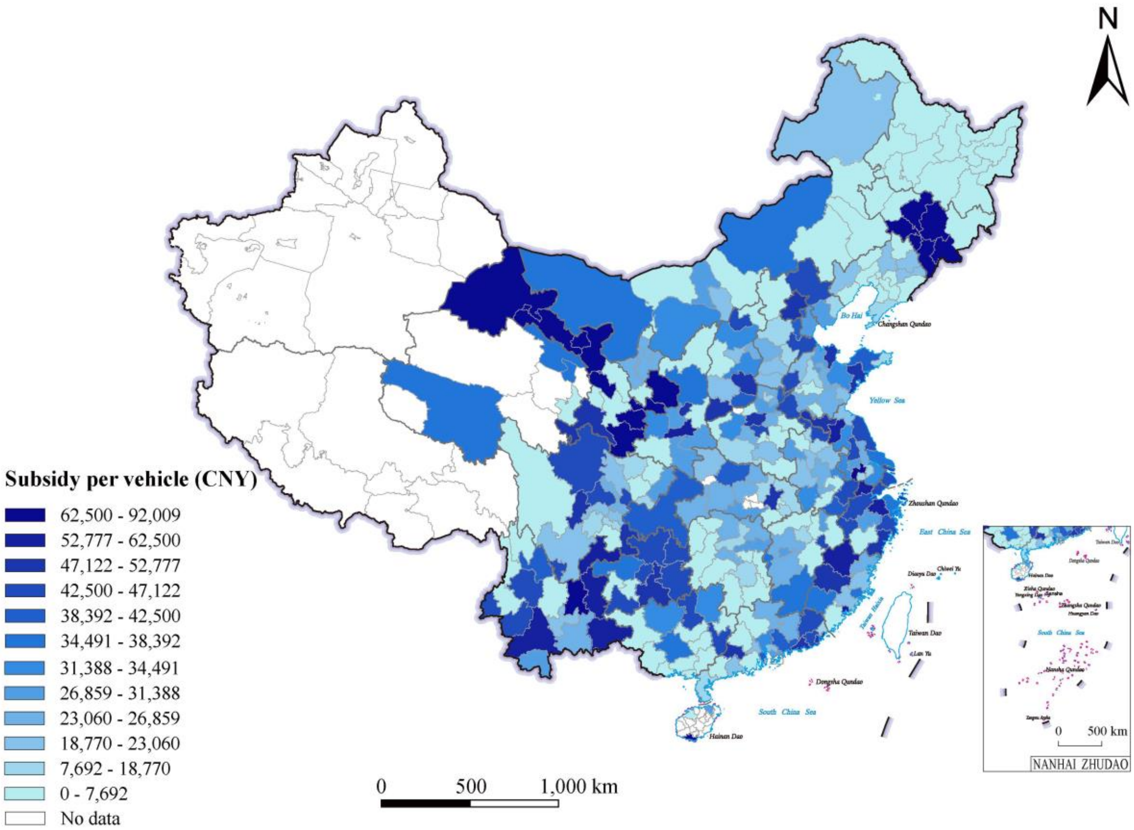
- *Electric driving range:* As shown in Table 1, vehicles with longer ranges have tended to receive higher subsidies.

[4] https://www.evpartner.com.

- *Location:* Subsidies have differed across cities due to different decisions of local governments.
- *Time*: Both the central and local per-vehicle subsidies have tended to decline over time.

Figure 3 presents the average purchase subsidy per vehicle by city in 2018.[5] The overall average was 36,890 CNY per vehicle. This was about 18.5% of the average manufacturer-recommended retail price for EVs of about 200,000 CNY in China between 2015 and 2018 (Li et al. 2022), which is quite large. The subsidies should therefore be expected to have a strong influence on consumer choices.

Figure 3 Average purchase subsidy per vehicle by city, 2018



Notes: Measured using the total payment of purchase subsidies from the central and local governments in a city divided by the number of new EV registrations. EVs include both domestically-produced and imported. Values are not deflated. No data = the number of new EV registrations in that city in 2018 was zero or the city is in an area for which data are not available. The definition of a city refers to the administrative division and includes rural and hinterland areas.

[5] Figure 3 is for 2018 as from July 2019 to the end of the dataset EV buyers have only received the central subsidy.

The average purchase subsidy per vehicle has varied across cities, for two reasons. First, different subsidies have been introduced by local governments. Second, the number of EV registrations in each range class varies by city. In some cities, long-range vehicles are relatively more popular. For example, Zhengzhou, the capital city of Henan province, had about 23,000 BEVs with an electric driving range of over 400 km registered in 2018, far more than other cities. These vehicles tend to receive a higher per-vehicle subsidy.

3.3 Other incentives

The analysis will also examine the effects of other EV incentives. Incentives that are the same nationwide, for example exemptions on the vehicle purchasing tax and on the V&V tax, are not included given that we control for time effects. Incentives that are time invariant at the city level over January 2016–December 2019 are also not included given we control for city fixed effects. An example is that EVs have enjoyed license fee exemptions in Hefei, Xian, and Shanghai. Another is that EVs have received an exemption on the fee for the owner's first purchase of compulsory insurance in Hefei and Xian.

Table 2 presents the other incentive policies controlled for in the regressions. Other than the NEV credits, these do not discriminate between domestically-produced and imported EVs. They vary by city and time. The charging subsidies also vary by electric driving range because Shenzhen applies different charging subsidies for BEVs and PHEVs. For tractability, some incentives such as charging discounts, parking fee benefits, and toll exemptions are measured as binary variables. Driving restriction exemptions are also measured in a binary way given this is a non-monetary incentive that is not easily quantified. Imported EVs are also subject to a 25% tariff and excluded from the sales tax exemption. In 2019 China imported 158,600 EVs (General Administration of Customs of China 2021), accounting for 12% of total EV sales (CAAM 2021).

Table 2 Other EV incentives used in regressions

Incentives	Explanation	Type	Variation
Charging subsidy (CNY/vehicle)	One-time subsidy for EV charging	Numeric	By range class, city, month
Charging discount	Discount on electricity price for EVs	Binary	By city, month
Vehicle replacement subsidy (CNY/vehicle)	One-time subsidy for switching from fuel vehicles to EVs	Numeric	By city, month
Parking fees benefit	EVs enjoy reduced or waived parking fees	Binary	By city, month
Driving restriction exemption	Fuel vehicles are restricted from driving on some days according to plate numbers in some cities, while EVs are exempt	Binary	By city, month
Toll exemption	EVs are exempt from road or bridge tolls	Binary	By city, month
Per-vehicle NEV credits	Manufacturers producing NEVs can obtain credits according to the dual credit policy	Numeric	By range class, month

Notes: If a policy is introduced intra-month, the binary variable equals 1 in that month.

Although we primarily focus on demand-side policies, we also control for NEV credits per vehicle. These vary by range class and time and are only for domestic-produced EVs. The specifics of the variation of this variable are:

- *Electric driving range:* Automakers producing higher electric driving range can receive more credits. For BEVs, the per-vehicle NEV credits equal $0.012 \times R + 0.8$, where R is the electric driving range in km. Automakers can obtain two credits per vehicle for PHEVs with an electric driving range equal to or above 50 km and zero credits if this range is under 50 km.
- *Time:* The dual credit policy was formally enacted in January 2019. The variable equals zero prior to that.

3.4 Knowledge of subsidies

Awareness of purchase subsidies may be a factor influencing the extent to which they induce EV adoption. According to a 2015 survey conducted by CAAM (2016), willingness to purchase EVs in China is highly correlated with knowledge of subsidy policies. Among respondents to this survey who were aware of subsidy policies, 57% were willing to consider purchasing EVs, while the share was only 38% among those who were not aware. Jenn et al. (2018) also found that consumer awareness is critical to the success of EV incentive programs in the US.

To construct a measure of consumer awareness, we used Python to scrape the Autohome forum, China's largest web forum for discussing vehicle related information.[6] We searched for posts that included both the word "subsidy" and a specific province name (in Chinese). We used the province given that many posts refer to the province rather than the city. We did not use "NEV" or "EV" (in full form) as search terms because posts often discuss specific models rather than these overall categories and because purchase subsidies did not exist for internal combustion engine vehicles during our sample period. While charging subsidies and vehicle replacement subsidies also exist, we assume that people who have knowledge of those other subsidies also know about the (larger) purchase subsidies.

We created two separate measures of consumer awareness of subsidies. Both reflect the number of posts and the level of interest that they arouse:

1. *Number of replies per 10,000 persons*: The total number of replies to all subsidy posts for a province in a month (plus the post itself). This varies by province and time.

2. *Readership number per 10,000 persons*: The cumulative readership of all subsidy posts for each province as of the access time, 11am 15 April 2021. This varies by province but not time. The timing of readership cannot be determined. Figure A1 in the Appendix presents the readership number per 10,000 persons by province. It shows sizeable variation in consumer awareness across provinces.

A concern is that sales of EVs may boost knowledge of the subsidy policy, implying reverse causality. We thus use the lag of the consumer awareness index (Bellemare et al. 2017; Leszczensky and Wolbring 2019). We proceed to include the consumer awareness variables and their interactions with the purchase subsidy variable. The per-vehicle purchase subsidy and the controls are also included separately.

3.5 Instrumental variable

There may be an endogeneity issue for the per-vehicle purchase subsidy given that third factors may influence both per-vehicle subsidy rates and new EV registration numbers. For example, cities with strong green preferences might have low local per-vehicle subsidies given that a relatively high number of new EV registrations is anyway expected. We consequently

[6] See https://club.autohome.com.cn. The information was accessed at approximately 11am 15 April 2021 (UTC+8:00).

instrument the per-vehicle subsidy rate using a post-ending of local subsidies dummy, set to 1 after July 2019 in cities that previously had local subsidies and 0 otherwise. Because the decision to end all local subsidies was made by the central government and had different implications for average subsidy levels in each city (varying based on cities' historical decisions to introduce local subsidies), the instrument provides a useful source of identifying variation. The instrument varies two-dimensionally: by city and month.

3.6 City tier

In 2020, financial news portal Diyicaijing classified 337 cities in mainland China into 6 tiers: tier 1, new tier 1, tier 2, tier 3, tier 4, and tier 5. The criteria for this categorization include a city's business resources, potential to function as a hub, activities for residents, lifestyle diversity, and future adaptability (China Daily 2019). While the tiers are not official classifications of China's government, Diyicaijing's classification is often referenced by the media and citizens. A higher tier refers to smaller and less-developed cities. The city tier index in this study is measured as an increasing sequence from 1 to 6.

3.7 Descriptive statistics

Table 3 shows summary statistics for the numeric variables used in the study. The three-dimensional dataset consists of more than 120,000 observations (by range class-city-month). The median values for the numbers of domestically-produced and imported new EV registrations are both 0, as a large number of cities did not have any new EV uptake in a specific range class and month during the sample period.

Variable definitions and data sources are shown in the Appendix. Table A1 also shows the correlation coefficients between several variables used in the estimations. Most of the coefficients are around or below 0.1 in absolute value, indicating that the independent variables are not overly strongly correlated.

Table 3 Summary statistics, monthly data

Variable	Observations	Mean	Median	Std. dev.	Min	Max
New EV registrations (domestically-produced)	121,344	21.58	0	235.89	0	14,380
New EV registrations (imported)	121,344	1.13	0	17.67	0	1,619
Purchase subsidy per vehicle (1,000 CNY/vehicle, real)	121,344	31.02	30.9	24.7	0	110.7
Charging discount (binary)	121,344	0.02	0	0.12	0	1
Vehicle replacement subsidy per vehicle (CNY/vehicle, real)	121,344	110.9	0	1,210.1	0	16,109
Charging subsidy per vehicle (CNY/vehicle, real)	121,344	37.2	0	520.04	0	10,000
Parking fees benefit (binary)	121,344	0.13	0	0.34	0	1
Driving restriction exemption (binary)	121,344	0.03	0	0.17	0	1
Toll exemption (binary)	121,344	0.03	0	0.16	0	1
Per-vehicle NEV credits	121,344	0.25	0	0.47	0	2
Consumer awareness index 1	1,095	0.009	0.004	0.02	0.0001	0.624
Consumer awareness index 2	29	108.8	105.1	80.6	2.2	721.7

Source: Variable definitions and data sources are in the Appendix. *Notes*: Domestically-produced and imported EV new registrations are both measured three-dimensionally: by range class, city, and month. The per-vehicle purchase subsidy, vehicle replacement subsidy, and one-time charging subsidy were deflated to a 2016 base using the CPI for China. The statistics for the consumer awareness indexes are for available data points rather than the full estimation sample.

4. Model

4.1 Basic model

The effect of subsidies on new EV registrations is investigated using the following three-dimensional model:

$$R_{r,i,t} = \alpha + \beta_1 S_{r,i,t} + X'_{r,i,t}\varphi + M_m + Y_y + \gamma_r + \delta_i + \varepsilon_{r,i,t} \quad (1)$$

where $R_{r,i,t}$ is the number of new EVs registered in range class r in city i and month t. S is the real purchase subsidy per vehicle deflated to 2016 prices in 1,000 CNY, measured using the average across vehicles in each range. X is a set of other incentives for EVs, as shown in Table 2.

Fixed effects are included by electric driving range class, city, and time to control for unobserved characteristics that vary only by each dimension. Specifically, month-of-year fixed effects (M) are included to control for seasonal factors; year fixed effects (Y) to control for yearly factors common to all range types in each city, such as the state of China's economy; city fixed effects (δ) to control for cross-sectional variation that does not change over time; and range class fixed effects (γ) to absorb time-invariant range-specific heterogeneity that may be correlated with subsidies. Specific product attributes, such as the vehicle purchase price, are not controlled for directly but are partly picked up by the range class fixed effects. Standard errors are clustered at the city×range level as local subsidy rates are decided at this level and to allow for autocorrelation for particular EV range types within a city. ε is an error term.

Several estimators are used. First, a fixed-effects LR estimator with an unlogged dependent variable is estimated. Month-of-year fixed effects and year fixed effects are then replaced by month fixed effects, which involves more controls.[7] Three sets of two-dimensional fixed effects are then included separately:

- *City × year fixed effects* to control for unobserved differences in EV registrations in each city in each year, such as due to differences in population growth.

- *City × range fixed effects* to control for unobserved differences in EV registrations in each range class in each city, such as due to local preferences for longer-range EVs.

- *Range × year fixed effects* to control for unobserved differences in EV registrations in each range class in each year, such as due to technological progress and consumer trends. The NEV credits variable is omitted from this specification to avoid perfect collinearity.

A fixed-effect NB estimator is then used, as suitable for a count dependent variable displaying over-dispersion (Cameron and Trivedi 1998). A log (x+1) transformation is not used as it may lead to different results than a log (x+0.1) or other transformation, especially given there are many zeros (O'Hara and Kotze 2010). We do not exclude observations of zero given that these are true zeros rather than missing observations. The NB estimator has often been used in related studies using count dependent variables such as the studies of car ownership of Oyedepo and Etu (2016) and Meelen et al. (2019). β_1 in the NB estimations can be interpreted as follows: for a one unit change in S, the log of the dependent variable is expected to change by β_1, holding the other variables constant.

[7] Month-of-year fixed effects refer to 11 fixed effects to remove monthly seasonality. Month fixed effects refer to a separate fixed effect for each actual month, i.e. month-by-year. Month fixed effects are able to control for temporal shocks that are common across cities, such as common changes in gasoline prices. Gasoline prices are known to be relevant for vehicle adoption (Burke and Nishitateno 2013).

In order to address potential endogeneity issues, we then instrument the three-dimensional average per-vehicle subsidy rate using a post-ending of local subsidies dummy. The cancellation of local subsidies was decided by the central government and thus likely to be plausibly exogenous at the local level. A concern is that cities that had local subsidies may have enhanced other local EV incentive and promotion approaches when the local subsidies were cancelled, however we control for key other policies. As the cancellation of local subsidies was announced on 26 March 2019 and not implemented until the start of July 2019, there is also the potential that consumers may have brought forward their purchases. We therefore exclude the three-month transition period April to June 2019 and also July 2019 from the sample used for the IV regressions.

In additional specifications, we use the differenced generalized method of moments (GMM) (Arellano and Bond 1991) and system GMM (Arellano and Bover 1995) estimators as alternative approaches to address endogeneity concerns.[8] These approaches use lagged internal instruments to seek consistent estimates of the causal effects of per-vehicle subsidies on EV registrations. We also use the novel bounding approach of Oster (2019) as a check on potential omitted variable bias in the LR estimations.[9] This approach is based on analyzing movements in coefficient values after the inclusion of controls.

4.2 Heterogeneity analysis

We proceed to investigate the importance of consumer awareness of EV purchase subsidies for their impact. The expectation is that the coefficients on the interactions between the consumer awareness variables and the purchase subsidy variable will be positive, as purchase subsidies are likely to induce greater uptake of EVs if there is strong consumer knowledge of the subsidies. An interaction with a city tier variable is then included, as Chinese cities differ in terms of infrastructure and purchasing power – hence, exploring how the effect of the subsidy policy on EV adoption varies by city size is also of interest. We also present estimations including an interaction between the purchase subsidy and a monthly trend to explore if the influence of purchase subsidies on EV uptake has changed over time. The monthly trend is also controlled for separately, with use of month-of-year fixed effects rather than month-by-year fixed effects meaning that it is not perfect collinearity with the time fixed effects.

[8] System GMM augments differenced GMM by estimating simultaneously in differences and levels.
[9] The results are calculated using the Stata commands *psacalc* and *psacalc2* from Oster (2019). These are for linear regressions.

We additionally explore estimations that compare the effects of domestic-vehicle purchase subsidies on registrations of domestically-produced EVs, imported EVs, and all EVs. We here use a four-dimensional dataset, using separate data for domestically-produced and imported EVs and arranged by range class, city, and month. Interactions between the purchase subsidy variable and both (a) a domestically-produced dummy and (b) an imported dummy are included. For effects on the total number of EV registrations, a three-dimensional dataset is again used.

4.3 Robustness checks

Several additional robustness checks will be reported. We first exclude institutional-buyer registrations from our dependent variable. From 2019, institutional buyers were subject to reduced subsidy rates, with the per-vehicle central subsidy being restricted to 70% of that for individual buyers (MOF of China 2019). Some local governments also provided different incentive policies for institutional buyers. We find a similar result when institutional purchases are excluded.

We also explore using the maximum per-vehicle subsidy in a city, as used in some prior research such as that of Ma et al. (2017). A two-dimensional dataset using an NB estimator is used. Finally, the effect of purchase subsidies on the ratio of EV registrations to total passenger vehicle registrations is presented. A two-dimensional city-month dataset is used given the electric driving range dimension is not relevant for non-EVs. An LR estimator is applied given that the dependent variable is a ratio.

5. Results

5.1 Main results

Table 4 presents monthly estimations for new registrations of domestically-produced EVs. Columns 1–6 show the results for a three-dimensional dataset (range-city-month), and columns 7–8 for a two-dimensional dataset (city-month). It is evident that the effects of purchase subsidies on EV registrations are consistently positive and statistically significant, suggesting that a higher per-vehicle purchase subsidy is associated with a greater number of new domestically-produced EV registrations, holding the other factors constant.

Column 1 of Table 4 presents a fixed-effect LR estimation controlling for range fixed effects, city fixed effects, month-of-year fixed effects, and year fixed effects. The coefficient on the purchase subsidy is 0.35, suggesting that a 1,000 CNY increase in the per-vehicle purchase subsidy has on average led to about 0.35 more new domestically-produced EVs being registered for a range class in a city in a month, all else equal. In column 2, the coefficient on the per-vehicle subsidy in an LR controlling for month fixed effects is 0.23.

Columns 3–5 of Table 4 control for various two-dimensional fixed effects, producing slightly larger coefficients than column 2. Specifically, when controlling for city × year fixed effects in column 3, the coefficient on the subsidy term is about 0.51. The result in column 4 with city × year fixed effects is 0.31, similar to when controlling for single-dimensional fixed effects in column 1. The coefficient on the subsidy controlling for range × year fixed effects in column 5 is 0.49. The larger point estimates when controlling for the interaction term between year and city/range fixed effects are likely to be due to unobserved differences in EV registrations in each city or range class in each year that may be correlated with the per-vehicle subsidy rate.

For the two-dimensional LR estimation in column 7 of Table 4, the coefficient on the purchase subsidy is 7.06. This suggests that a 1,000 CNY increase in the per-vehicle purchase subsidy has on average led to about 85 more new domestically-produced EVs being registered per city per year (=7.06×12 months), all else equal. The effect is larger than the three-dimensional estimate in column 1, where a coefficient of 0.35 implies about 34 more new domestically-produced EVs being registered per city per year due to the same increase in the per-vehicle purchase subsidy (=0.35×8 range types×12 months).

Column 6 of Table 4 presents a three-dimensional NB specification. The coefficient for the per-vehicle purchase subsidy variable is 0.061, significantly different from zero at the 1% level. For the two-dimensional dataset, the coefficient in an NB specification in column 8 is 0.045. This suggests that a 1,000 CNY increase in the per-vehicle purchase subsidy has on average led to new domestically-produced EV registrations increasing by about 5% (=(exp(0.045) – 1)×100), holding the other variables constant. The NB results are slightly larger effects than those from the LR estimator.[10]

[10] The mean registrations of new domestic EVs is 21.58. 21.58 × 8 ranges × 5% = 8.63, which is larger than 7.06.

Table 4 Results for domestically-produced EVs, monthly data

Dependent variable: New domestically-produced EV registrations$_{r,i,t/i,t}$								
Specification	Three-dimensional (range-city-month)						Two-dimensional (city-month)	
	LR	LR	LR	LR	LR	NB	LR	NB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t/i,t}$	0.348***	0.227*	0.515***	0.313**	0.486***	0.061***	7.061***	0.045**
	(0.122)	(0.121)	(0.140)	(0.128)	(0.151)	(0.007)	(2.219)	(0.023)
Vehicle replacement subsidy per vehicle (CNY, real)$_{r,i,t/i,t}$	0.015**	0.015**	–0.006	0.015**	0.015**	0.000***	–0.127	0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.000)	(0.118)	(0.000)
Charging subsidy per vehicle (CNY, real)$_{i,t}$	0.008	0.008	–0.000	0.009*	0.008	0.000	–0.004	0.000
	(0.005)	(0.005)	(0.001)	(0.005)	(0.005)	(0.000)	(0.004)	(0.000)
Charging discount (binary)$_{i,t}$	222.679**	221.405**	218.545**	224.929**	221.710**	0.478	1731.024***	–0.814
	(89.688)	(89.597)	(107.284)	(89.586)	(88.607)	(0.610)	(228.823)	(7.197)
Driving restriction exemption (binary)$_{i,t}$	–6.357	–7.054	93.104**	–7.917	–5.734	–0.113	736.234*	–0.849
	(32.210)	(32.159)	(44.571)	(32.125)	(30.762)	(0.400)	(407.792)	(0.714)
Parking fee benefits (binary)$_{i,t}$	13.564	13.076	46.211	13.080	13.500	–0.347	402.779	–1.175
	(10.586)	(10.444)	(31.508)	(10.558)	(10.452)	(0.534)	(302.129)	(2.136)
Toll exemption (binary)$_{i,t}$	–26.235	–27.657	96.223	–26.333	–24.171	–0.649	745.843***	0.280
	(27.281)	(27.182)	(161.427)	(27.163)	(27.222)	(0.902)	(201.719)	(2.791)
Per-vehicle NEV credits$_{r,t}$	8.692	9.332	7.846	8.874		3.068***		
	(12.142)	(12.139)	(10.630)	(12.000)		(0.335)		
Range fixed effects	Yes	Yes	Yes	No	No	Yes	No	No
City fixed effects	Yes	Yes	No	No	Yes	Yes	No	Yes
Month-of-year fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	No	Yes	No	Yes	No	No
Month fixed effects	No	Yes	No	No	No	No	No	No
City × year fixed effects	No	No	Yes	No	No	No	Yes	Yes
City × range fixed effects	No	No	No	Yes	No	No	No	No
Range × year fixed effects	No	No	No	No	Yes	No	No	No
Adjusted R^2	0.03	0.04	0.06	0.11	0.04		0.25	
Observations	121,344	121,344	121,344	121,344	121,344	121,344	15,168	15,168

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Robust standard errors are shown in parentheses and are clustered at the city-range level in columns 1–6 and at the city level in columns 7–8. NEV credits are not controlled for in the two-dimensional regressions given that the variable varies by range.

The coefficients on the per-vehicle vehicle replacement subsidy and the charging discount dummy variable tend to be positive and significant in most columns. The estimates on per-vehicle NEV credits are positive, although are not always statistically significant. We do not find strong effects for other incentives.

5.2 IV results

Table 5 displays linear IV results for a specification in which the post-ending of local subsidy dummy is used to instrument the per-vehicle purchase subsidy. As discussed, four months of the sample are excluded from the IV estimations.[11] The IV estimates are larger than the OLS results (see column 1 of Table 5 versus column 1 of Table 4, which include the same fixed effects). This is perhaps because the local average treatment effect of the subsidy removal was large or due to underlying bias in the OLS estimations. The significant first-stage coefficients suggest that the instrument is negatively correlated with the per-vehicle purchase subsidy, as expected given that the ending of local subsidies directly reduced the average per-vehicle subsidy. Specifically, the cancellation of local subsidies on average reduced the per-vehicle purchase subsidy by about 20,163 CNY. This was about 73% of the average per-vehicle subsidy that had existed in June 2019 (27,678 CNY). Stock and Yogo (2005) tests confirm that the instrument provides strong first-stage identification.

Results using differenced and system GMM are presented in Table A2 of the Appendix. The lagged number of EV registrations and higher order lags terms are used as internal instruments in the GMM estimations in columns 1 and 2. The post-ending of local subsidies dummy is also used as an external instrument in additional GMM estimations in columns 3 and 4. The regression results in Table A2 continue to indicate that the per-vehicle subsidy has a positive effect on EV registrations. The p-values for the Arellano and Bond (1991) test do not provide evidence of second-order autocorrelation in first-differences. We also fail to reject the null of the Hansen (1982) J test that the system-GMM overidentifying restrictions are valid.

We now conduct robust “approximate exogenous IV” inference under the condition of relaxing the exogeneity of IVs proposed by Conley et al. (2012). Specifically, the union of confidence intervals (UCI) and the local to zero (LTZ) approaches are used to test the robustness of results if the IV is not completely exogenous. The robust confidence interval for the per-vehicle

[11] Non-IV results excluding the three-month transition period and the month following the removal of local subsidies remain similar to those using the full sample.

purchase subsidy effect obtained by the UCI method is (0.427, 3.556). The coefficient using the LTZ approach is significantly positive (0.741). These indicate that the IV results remain similar in the approximately exogenous case.

Results using the approach of Oster (2019) to address omitted variables concerns are reported in Table A3 of the Appendix. It is found that the bounded sets for the coefficient of the purchase subsidy variable are positive and exclude zero. This provides evidence that the finding of a positive effect of subsidies is relatively robust even in the face of potentially important unobserved factors.

Table 5 IV results for domestically-produced EVs, LR estimator, monthly data

Dependent variable: New domestically-produced EV registrations$_{r,i,t/i,t}$				
Specification	Three-dimensional model		Two-dimensional model	
	(1)	(2)	(3)	(4)
Purchase subsidy per vehicle	0.744***	1.528***	5.939***	12.210***
('000 CNY, real)$_{r,i,t/i,t}$	(0.160)	(0.273)	(1.484)	(2.266)
Vehicle replacement subsidy	0.015***	–0.008*	0.118***	–0.128
per vehicle (CNY, real)$_{r,i,t/i,t}$	(0.003)	(0.004)	(0.029)	(0.087)
Charging subsidy per vehicle	0.008***	0.000	0.066***	–0.001
(CNY, real)$_{i,t}$	(0.003)	(0.001)	(0.025)	(0.015)
Charging discount (binary)$_{i,t}$	227.918***	213.623	1837.755***	1698.572
	(52.345)	(146.518)	(438.834)	(1281.616)
Driving restriction exemption	10.665	88.996**	80.928	705.818**
(binary)$_{i,t}$	(26.046)	(38.901)	(208.818)	(338.831)
Parking fee benefits (binary)$_{i,t}$	12.785*	47.784**	105.243	416.761*
	(7.114)	(23.571)	(66.752)	(217.039)
Toll exemption (binary)$_{i,t}$	–19.057	91.627	–156.692	717.228
	(13.401)	(121.578)	(120.797)	(961.888)
Per-vehicle NEV credits$_{r,t}$	2.664	–0.673		
	(5.359)	(5.474)		
Range fixed effects	Yes	Yes	No	No
City fixed effects	Yes	No	Yes	No
Month-of-year fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No
City × year fixed effects	No	Yes	No	Yes
City × range fixed effects	No	No	No	No
Range × year fixed effects	No	No	No	No
R^2	0.002	–0.001	0.010	0.009
Observations	111,232	111,232	13,904	13,904
Instrumented variable: Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t/i,t}$				
Instrumental variable: Post-ending of local subsidy dummy$_{i,t}$				
Coefficient on instrument	–20.163***	–23.481***	–20.165***	–23.480***
F statistic on instrument	6,425.51	6,938.48	5,382.55	11,243.53

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Robust standard errors are shown in parentheses and are clustered at the city-range level in columns 1–2 and at the city level in columns 3–4. The null of weak instruments is rejected if the *F* statistic on the instruments exceeds the Stock-Yogo critical value. The Stock-Yogo 5% critical value for 10% maximal IV size is 16.38. NEV credits are dropped in the two-dimensional regression.

5.3 Heterogeneity analysis

Table 6 presents heterogeneity analyses using the NB estimator. Column 1 employs the first consumer awareness measure: the number of replies to subsidy-related posts on the Autohome forum per 10,000 persons. A one-month lag is used, and this is also interacted with the per-vehicle purchase subsidy variable. Column 2 uses the second consumer awareness measure: the cumulative readership of posts per 10,000 persons. The coefficients on the interaction between the EV purchase subsidy and the consumer awareness indexes in columns 1–2 are positive and statistically significant, suggesting that greater consumer awareness is associated with higher proportional purchase subsidy effectiveness. This is consistent with the findings of Qian et al. (2019), who used a survey-based method.

Column 3 of Table 6 investigates potential heterogeneity by city tier by including an interaction between the EV purchase subsidy and the city tier index. The coefficient on the interaction term is positive and significant at the 1% level. Specifically, a 1,000 CNY increase in the per-vehicle purchase subsidy on average leads to about an additional 0.7 percentage point ($=(\exp(0.007) - 1)\times100$) increase in new EV registrations for every unit increase in city tier. Given that higher city tiers are for smaller and less developed cities, this suggests that EV purchase subsidies have a larger proportional effect on EV uptake in smaller cities. This may be because smaller cities have lower development levels.

Column 4 of Table 6 includes an interaction between the per-vehicle subsidy and a monthly time trend. The coefficient is positive and statistically significant, implying that the proportional effect of EV purchase subsidies (per ’000 CNY) has increased over time. This is consistent with the finding of Li et al. (2022) that purchase subsidies played a larger role in stimulating EV sales in China during 2017 and 2018 than in the prior two years. The result may be linked to declines in EV prices and maturation of the market, including improvements in vehicle quality and variety.

Table 6 Heterogeneity analysis for domestically-produced EVs, NB estimator, monthly data

Dependent variable: New domestically-produced EV registrations$_{r,i,t}$				
	(1)	(2)	(3)	(4)
Specification	Consumer awareness index 1	Consumer awareness index 2	City tier	Year
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t}$	0.060***	0.004	0.033***	–0.001
	(0.008)	(0.005)	(0.012)	(0.009)
Purchase subsidy$_{r,i,t}$ × consumer awareness$_{i,t/t}$	0.138***	0.00005***		
	(0.039)	(0.000)		
Consumer awareness$_{i,t/i}$	–13.238***	–0.005***		
	(2.297)	(0.001)		
Purchase subsidy$_{r,i,t}$ × City tier$_i$			0.007***	
			(0.002)	
Purchase subsidy$_{r,i,t}$ × Monthly trend$_t$				0.002***
				(0.000)
Monthly trend$_t$				–13.438***
				(0.0903)
Vehicle replacement subsidy per vehicle (CNY, real)$_{r,i,t}$	0.0003***	–0.0001**	0.0002**	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Charging subsidy per vehicle (CNY, real)$_{i,t}$	0.0003***	0.0003**	0.000	0.000
	(0.0001)	(0.0001)	(0.000)	(0.000)
Charging discount (binary)$_{i,t}$	1.409***	1.581***	0.273	0.582
	(0.481)	(0.553)	(0.726)	(0.437)
Driving restriction exemption (binary)$_{i,t}$	–0.567	2.264***	–0.212	–0.073
	(0.446)	(0.393)	(0.405)	(0.433)
Parking fee benefits (binary)$_{i,t}$	0.200	–0.460*	–0.378	–0.401
	(0.489)	(0.233)	(0.545)	(0.543)
Toll exemption (binary)$_{i,t}$	–1.635*	2.520***	–0.661	–0.840
	(0.864)	(0.414)	(0.897)	(0.879)
Per-vehicle NEV credits$_{r,t}$	3.363***	–0.794**	3.122***	3.368***
	(0.348)	(0.369)	(0.341)	(0.357)
Range fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	No	Yes	Yes
Month-of-year fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	92,537	121,344	121,344	121,344

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Robust standard errors are shown in parentheses and are clustered at the city-range level. All regressions use three-dimensional models and control for month dummies, city fixed effects, and range class fixed effects. City fixed effects are not controlled for in column 2 to avoid perfect collinearity with consumer awareness index 2. The time trend starts at 1 in January 2016 and increases by one per month.

5.4 Effects for domestically-produced versus imported EVs

Table 7 reports separate effects for registrations of domestically-produced and imported EVs.[12] Throughout, the purchase subsidy variable is for domestically-produced vehicles registered in each range class, city, and month. The effect on new registrations of domestically-produced

[12] All interaction component terms are also included separately in each regression.

EVs using the monthly dataset in column 1 is positive and statistically significant. The coefficient for imported EVs is negative and statistically significant. Specifically, a 1,000 CNY increase in the per-vehicle purchase subsidy on domestically-produced EVs in the same range, city, and month has on average led to a reduction in the corresponding number of imported EV registrations of about 2% (=(exp(0.023) – 1)×100), holding the other variables constant. The null that the effects for these two groups are equal can be rejected at the 1% significance level. The results thus imply that higher EV purchase subsidies for domestic EVs discourage uptake of imported EVs. This is in line with expectations.

Table 7 Effects for domestically-produced versus imported EVs, NB estimator

Dependent variable: New EV registrations$_{r,i,d,t/r,i,t}$				
	Monthly		Quarterly	
	Comparison	Total EVs	Comparison	Total EVs
	(1)	(2)	(3)	(4)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t}$ × Domestic dummy	0.087***		0.102***	
	(0.005)		(0.006)	
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t}$ × Imported dummy	–0.023***		–0.021***	
	(0.004)		(0.005)	
	[0.000]		[0.000]	
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t}$		0.034***		0.039***
		(0.006)		(0.006)
Vehicle replacement subsidy per vehicle (CNY, real)$_{r,i,t}$	0.0001**	0.0002***	0.0001**	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Charging subsidy per vehicle (CNY, real)$_{i,t}$	–0.000	0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Charging discount (binary)$_{i,t}$	0.521	0.920*	0.244	0.832
	(0.430)	(0.491)	(0.405)	(0.677)
Driving restriction exemption (binary)$_{i,t}$	0.576*	0.130	0.496	0.384
	(0.294)	(0.366)	(0.351)	(0.454)
Parking fee benefits (binary)$_{i,t}$	–1.511***	–0.951*	–1.811***	–1.092*
	(0.500)	(0.533)	(0.527)	(0.602)
Toll exemption (binary)$_{i,t}$	–0.157	0.215	0.066	0.127
	(0.631)	(0.729)	(0.650)	(0.795)
Per-vehicle NEV credits$_{r,t}$	2.322***	3.032***	2.440***	3.338***
	(0.137)	(0.317)	(0.157)	(0.359)
Range fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	No	No
Quarter fixed effects	No	No	Yes	Yes
Observations	242,688	121,344	80,896	40,448

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Robust standard errors are shown in parentheses and are clustered at the city-range level. Columns 1 and 3 use four-dimensional models. Columns 2 and 4 use three-dimensional models. Figures in square brackets are *p*-values for tests of equality to the coefficient for domestically-produced EVs. An identical estimate to column 2 for domestic vehicles provides a coefficient of 0.059***.

Column 2 of Table 7 presents a monthly estimation for the total number of registrations of new EVs. It suggests that a 1,000 CNY increase in the average purchase subsidy per domestically-produced EV has on average led to the total number of new EV registrations increasing by about 3% (=(exp(0.034) – 1)×100), holding the other variables constant. As expected, this is in-between the effects for domestic and imported EVs.

In the quarterly estimations in Table 7, the effect on domestically-produced EVs is larger than using a monthly estimation.[13] As expected, the magnitude falls between the effect size for domestically-produced EVs and that for imported EVs. The quarterly estimate in column 4 suggests that a 1,000 CNY increase in the per-vehicle purchase subsidy on average to about 29 additional total new EVs registered per year per city (=4%×22.71×4 quarters×8 range classes). While this is not a large number, a 1,000 CNY increase in the per-vehicle subsidy is also not large. Considering a larger per-vehicle subsidy variation, an increase by the mean per-vehicle purchase subsidy of 31,000 CNY (see Table 3) in our sample period would on average be responsible for an increase in total EV registrations of about 899 per city per year. This would equal about 32.4% of the average number of new EVs registered per city in 2019 (2,772).

The estimated effect of EV purchase subsidies on total EV uptake can be compared to the findings of Jenn et al. (2018) for the US and Azarafshar and Vermeulen (2020) for Canada. Jenn et al. (2018) found that every US$1,000 (about 10% of the per-vehicle subsidy in the US) offered as a rebate or tax credit increased average sales of EVs by about 2.6%. Azarafshar and Vermeulen (2020) found that a C$1,000 (about 1% of an EV's base price in Canada) increase in incentives on average caused sales of new EVs to increase by 5–8%. Our result is larger than the finding of Ma et al. (2017) for China. There are differences in method to consider, however, including that Ma et al. (2017) used the ceiling per-vehicle purchase subsidy in each city rather than the average per-vehicle subsidy.

5.5 Robustness checks

Column 1 of Table 8 is an NB estimation that restricts EV registrations to only non-institutional registrations. The result is similar to that for total buyers in column 6 of Table 4. Column 2 uses the maximum rather than average subsidy per vehicle. A positive and statistically significant coefficient on the per-vehicle purchase subsidy is again obtained; specifically, a

[13] Table A4 in the Appendix presents results controlling for up to three months of lags of the per-vehicle purchase subsidies. The summed coefficients for the purchase subsidy per vehicle are shown in the base of the table and are larger than the coefficient in the static specification in column 6 of Table 4. Hence there is some evidence of a lagged effect. The quarterly estimation in Table 7 subsumes intra-quarter lagged effects.

1,000 CNY increase in the maximum per-vehicle subsidy is on average associated with registrations of new domestically-produced EVs increasing by about 4%. This is smaller than the result in column 8 of Table 4 when using the average per-vehicle subsidy.

Table 8 Robustness checks for domestically-produced EVs

Dependent variable: New domestically-produced EV registrations$_{r,i,t/i,t}$			
Specification	Individual buyers	Maximum subsidy	EV market penetration rate (%)
	(1)	(2)	(3)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t/i,t}$	0.063*** (0.007)	0.035** (0.014)	0.048*** (0.015)
Vehicle replacement subsidy per vehicle (CNY, real)$_{r,i,t/i,t}$	0.0002*** (0.0001)	0.000 (0.001)	0.000 (0.000)
Charging subsidy per vehicle (CNY, real)$_{i,t}$	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Charging discount (binary)$_{i,t}$	0.797 (0.637)	–0.866 (7.742)	4.475** (2.085)
Driving restriction exemption (binary)$_{i,t}$	–0.463 (0.408)	–0.766 (0.753)	–0.135 (1.125)
Parking fee benefits (binary)$_{i,t}$	–0.217 (0.538)	–1.226 (2.308)	–0.712 (1.193)
Toll exemption (binary)$_{i,t}$	–0.355 (1.004)	0.358 (3.017)	–1.198 (4.313)
Per-vehicle NEV credits$_{r,t}$	2.823*** (0.326)		
Range fixed effects	Yes	No	No
City fixed effects	Yes	Yes	Yes
Month-of-year fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	121,344	15,168	15,079

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Columns 1–2 employ the NB estimator and column 3 uses an LR estimator. Robust standard errors are shown in parentheses and are clustered at the city-range level in column 1 using a three-dimensional dataset and at the city level in columns 2–3 using a two-dimensional dataset. NEV credits are dropped in two-dimensional regressions.

Column 3 of Table 8 presents the effect of purchase subsidies on the ratio of EV registrations to total passenger vehicle registrations. A positive and statistically significant coefficient for the per-vehicle purchase subsidy is again obtained. Specifically, a 1,000 CNY increase in the per-vehicle purchase subsidy on domestically-produced EVs on average leads to a 0.05 percentage point increase in the share of vehicle registrations that are EVs, holding the other variables constant.

6. Subsidy cost per tonne carbon dioxide emission reduction

We now provide a calculation of the subsidy cost-effectiveness of China's purchase subsidy scheme in reducing CO_2 emissions, using a similar method to Azarafshar and Vermeulen (2020) in a study for Canada.[14] We use the finding that a 1,000 CNY increase in the per-vehicle purchase subsidy for domestic vehicles has on average boosted total (not only domestic-model) uptake of new EVs by about 3% based on the result in column 2 of Table 7. The CO_2 emission reductions are calculated using the difference between the future lifetime-of-use emissions of BEVs and PHEVs resulting from a 1,000 CNY increase in purchase subsidies per vehicle and the future lifetime-of-use emissions generated under a counterfactual in which these were gasoline vehicles. The calculations are for 2019. There were a total of 688,569 new passenger BEV registrations and 209,353 new passenger PHEV registrations in mainland China outside the Xinjiang and Tibet Autonomous Regions that year.

If there were a 1,000 CNY per vehicle increase in the EV purchase subsidies in 2019, the estimates suggest that this would have led to about an additional 20,657 registrations of BEVs (based on a 3% increase in total BEV registrations). This would involve lifetime-of-use CO_2 emissions generated from electricity of about 263,900 tonnes, the product of:

- A fleet average fuel economy of 18.1 kilowatt-hour (kWh)/100km for BEVs in China.[15]
- An average annual VKT of 8,140 km per vehicle for BEVs in China.
- An average carbon intensity of electricity of 598g CO_2/kWh in 2019 in China (IEA 2020b).
- A 14.5-year average lifespan.[16]
- And the number of additional registrations of 20,657 BEVs.

If there were a 1,000 CNY per vehicle increase in EV purchase subsidies in 2019, this would have led to about an additional 6,281 registrations of PHEVs (based on a 3% increase in total

[14] The analysis is for the subsidy payment required per ton CO_2 avoided, not the economic cost.
[15] We use China's average fuel economy and annual vehicle kilometers travelled (VKT) data for BEVs from a survey conducted in 2018 by the National Big Data Alliance of NEVs (2019).
[16] From a large sample of survey on vehicle patterns, Hao et al. (2011) found that the average lifespan of passenger vehicles in China was 14.5 years. Peng et al. (2018) used this lifespan in their analysis. We assume for simplicity that a BEV, PHEV, and a conventional gasoline car will stay on the road for the same length of time.

PHEV registrations). This would involve lifetime-of-use CO_2 emissions generated from PHEVs (electricity plus gasoline) of about 211,353 tonnes, calculated as the sum of:

- CO_2 emissions generated from PHEVs running on electricity, using an average electricity requirement of 17.5 kWh/100km multiplied by the average annual electric-powered VKT per vehicle of 7,519 km multiplied by the average carbon intensity of electricity of 598g CO_2/kWh multiplied by a 14.5-year lifespan multiplied by 6,281 additional registrations of PHEVs.[17]

- CO_2 emissions generated from PHEVs running on gasoline, using a fleet average fuel economy of 8.87 liters/100km multiplied by the average annual gasoline-powered VKT per vehicle of 7,519 km multiplied by the carbon intensity of displaced emissions of 2.3 kg of CO_2 per liter of gasoline multiplied by a 14.5-year lifespan multiplied by 6,281 additional registrations of PHEVs.

In the counterfactual it is assumed that these vehicles would have been conventional gasoline vehicles. The lifetime-of-use CO_2 emissions generated from conventional gasoline vehicles is calculated to be about 750,540 tonnes, using the same VKT traveled by EVs, calculated as the sum of:

- A fleet average fuel economy of 8.57 litres/100km for gasoline vehicles in China, multiplied by an annual VKT of 8,140 km per vehicle (the average distance for BEVs), multiplied by a carbon intensity of displaced emissions of 2.3 kg of CO_2 per litre of gasoline, multiplied by the 14.5-year lifespan, multiplied by 20,657 additional gasoline vehicle rather than BEV registrations.[18]

- A fleet average fuel economy of 8.57 litres/100km for gasoline vehicles in China, multiplied by an annual VKT of 15,038 km per vehicle, multiplied by a carbon intensity of displaced emissions of 2.3 kg of CO_2 per litre of gasoline, multiplied by the 14.5-year

[17] China's average fuel economy and annual VKT data for PHEVs are also from National Big Data Alliance of NEVs (2019). There is no specific survey on the annual electric VKT of PHEVs in China, but to date they tend to travel further than BEVs because BEVs are mainly used for daily short-distance commuting given undeveloped charging infrastructure and long charging times (National Big Data Alliance of NEVs 2019). We follow Yang et al. (2021) and assume that the electric share of the annual total VKT for PHEVs is half.

[18] We use China's average fuel economy data for the conventional gasoline vehicles from a survey conducted in 2018 by Innovation Centre for Energy and Transportation (Mao et al. 2018).

lifespan, multiplied by 6,281 additional gasoline vehicle registrations rather than PHEV registrations.[19]

As a result, a 1,000 CNY increase in purchase subsidies per vehicle in 2019 would have led to the avoidance of about 275,287 tonnes of CO_2 emissions (over the subsequent 14.5-year assumed lifetime of the vehicles, and with no discount rate applied). Given that the higher subsidy rate would need to be paid for all (and not only marginal) sales, the required additional subsidy cost would be about 1,225.92 million CNY, the sum of:

- An *inframarginal cost* of 897.92 million CNY, which is the additional subsidy cost flowing to EVs that would have been registered anyway. This is calculated using the increase in the per-vehicle subsidy of 1,000 CNY multiplied by 897,922 new EV registrations in 2019.

- A *marginal cost* of 328.00 million CNY, which is the subsidy cost for the additional EVs that would have been registered as a result of the increase in the per-vehicle subsidy of 1,000 CNY. This is calculated using the sum of the average base subsidy of 11,176 CNY per vehicle across all new EVs in 2019 and 1,000 CNY increase in per-vehicle subsidy, multiplied by an additional 26,938 EVs.

Using an average carbon intensity of electricity of 598 gCO_2/kWh in 2019 in China, our calculation suggests that the subsidy cost of eliminating a tonne of CO_2 via an increase in the per-vehicle purchase subsidy was about 4,453 CNY. Using an exchange rate of 0.16 US$ per CNY, this converts to an implied carbon price of about US$712 per tonne CO_2.[20] This is similar to findings for the US for the period 2010–2014 of Xing et al. (2021), who calculated an EV subsidy cost of CO_2 emission reductions of more than US$700 per tonne. The result is larger than the finding for Canada of Azarafshar and Vermeulen (2020), who assessed the subsidy cost of reducing a tonne of CO_2 emissions via an increase in Canada's EV subsidy rate to be about C$480 (US$389) for the period 2012–2016. Our study uses more recent data when EVs

[19] We use the same annual VKT for PHEVs and gasoline vehicles in our calculations. Following Yang et al. (2021) that the annual electric VKT, 7,519 km, is half of the annual total VKT for PHEVs, the annual VKT for gasoline vehicles is thus assumed to be 15,038 km.
[20] When using the result in column 4 of Table 7 that a 1,000 CNY increase in the per-vehicle purchase subsidy has boosted total uptake of new EVs by about 4%, the per-tonne subsidy cost of CO_2 emission reductions is calculated to be 3,340 CNY (US$534).

were more competitive. A countervailing factor is that China's electricity mix is more than four times as carbon-intensive as Canada's.

Using a similar approach to the above, we calculate that a 1,000 CNY increase in the per-vehicle purchase subsidy in 2019 would have helped save about 264.4 million liters of lifetime gasoline use. This suggests the EV subsidy cost of saving a liter of gasoline via an increase in the per-vehicle purchase subsidy has been about 4.64 CNY (US$0.74). This is more cost-effective than what was estimated for the US by Peterson and Michalek (2013) and Sheldon and Dua (2019) in their analyses of subsidies for PHEVs.

Our calculation is back-of-the-envelope and does not consider CO_2 emissions in the vehicle production process. The calculation is also sensitive to assumptions such as the relevant emissions intensity of electricity to use. It is assumed that EV owners on average drive the same distance per year as drivers of gasoline vehicles, but EVs might actually be driven further given their low marginal cost of use (Zhang and Burke 2020) – especially as charging infrastructure matures. Nevertheless, the calculation provides an indicative assessment of the subsidy cost-effectiveness of China's purchase subsidies for EVs in achieving the aim of CO_2 emissions reductions.

A subsidy cost of US$712 per tonne CO_2 avoided is high. China's national emission trading system (ETS) made its debut on 16 July 2021 with an opening price of only US$7.4 per tonne (Raiser et al. 2021) and averaged about US$6.4 per tonne over the remainder of 2021 (Wang et al. 2022b). Most countries have a carbon price of less than US$50/t$CO_2$ (World Bank 2023). The calculation is also larger than the estimate of the country-level social cost of carbon (SCC) of US$24 per tonne of CO_2 for China and a median estimate of the global SCC of US$417 per tonne of CO_2 by Ricke et al. (2018). It is also higher than some findings for other clean technology subsidies. For example, Best et al. (2019) estimated that an increase in the subsidy rate for Australia's rooftop solar photovoltaic subsidy scheme reduces CO_2 emissions at a subsidy cost of about US$36 per tonne.

A key reason for a relatively high EV subsidy cost of abating CO_2 emissions in China is that the carbon intensity of China's electricity mix is higher than the global average of 475 gCO_2/kWh (IEA 2020b). This is due to high dependence on coal, which contributed 65% of China's electricity in 2019 (IEA 2020c). As the electricity grid decarbonizes, the benefits of EVs will increase. If the carbon intensity of electricity were zero, our estimates suggest that a

1,000 CNY increase in purchase subsidies per vehicle in 2019 would have led to the avoidance of about 610,836 tonnes of CO_2 emissions. The subsidy cost of mitigating CO_2 emissions would be reduced to about 2,007 CNY (US$321) per tonne.

While the subsidy cost of emissions reductions from China's EV purchase subsidies may be relatively high, there are other benefits of EV industry expansion, particularly in the long run. These include improving China's energy security and reducing local air pollution (Holland et al. 2016). There are also dynamic industry development benefits, with current efforts helping EVs to become mainstream. By developing the automotive industry and generating knowledge spillovers, China's EV subsidies generate broader benefits than the short-run contribution to CO_2 emissions reductions alone.

7. Conclusion

This study finds that increases in purchase subsidies for domestically-produced EVs have led to additional new registrations of these vehicles and discouraged uptake of imported EVs, and provides magnitudes of the effects. A key potential application of the results is to understand the increased competitive pressures that domestic EV manufacturers now face following the withdrawal of the central purchase subsidies. Our results are also relevant for understanding the extent to which the return of some local EV purchase subsidies in 2023 may affect registration numbers, and also how boosting consumer awareness of these subsidies could help to boost their impact.

The results of a counterfactual simulation indicate that the subsidy cost of reducing CO_2 emissions via an increase in the per-vehicle subsidy rate under China's purchase subsidy scheme has been about 4,453 CNY (US$712) per tonne. This is expensive, and higher than most estimates of the global SCC. However, a cost effectiveness analysis would be more favorable if China's electricity grid were to quickly decarbonize. Boosting the share of electricity generated from cleaner fuels is thus an important priority for sectoral decarbonization plans in China. It is also worth noting that there are dynamic and cross-border benefits from the take-off of China's EV sector, and other benefits for the environment and human health such as due to reduced local air pollution. By contributing to the early development of an important clean technology industry, the long-run benefits of China's EV subsidy program may well exceed the short-run benefits.

The findings are also relevant for other clean technology adoption efforts and for other countries that aim to promote adoption of EVs. Specifically, purchase subsidies are a useful approach to promote EV deployment, although involve considerable public funds. One option is to raise awareness of subsidies to ensure a strong effect on EV uptake while they are in place, although doing so would expand the required subsidy budget. Other results are also of relevance, such as the finding that China's EV charging discounts appear to have been positively associated with adoption of EVs.

A limitation of this study is the absence of a control for charging station infrastructure given data limitations. Future research – including at a more micro level – may be able to better consider this issue. Limited charging infrastructure is known to be a highly relevant constraint to the development of EV markets in some locations in China, especially smaller cities and rural areas (Ma et al. 2017; Li et al. 2022).

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Appendix

Variable definitions and sources

New EV registrations (domestically-produced): The number of new registrations of domestically-produced EV passenger vehicles. Measured by electric driving range class, city, and month. Heavier vehicles such as buses are not included.

New EV registrations (imported): The number of new registrations of imported EV passenger vehicles. Measured by electric driving range class, city, and month. Heavier vehicles such as buses are not included.

Purchase subsidy per vehicle (real): The sum of central and local subsidies for domestically-produced EVs per vehicle, averaged across new registrations of domestically-produced EVs, in '000 CNY. Measured by electric driving range class, city, and month. The CPI for China was used to adjust the price to a 2016 base. Source for CPI: Wind (2021).

Other incentives: See Table 2.

EV market penetration rate (%): The percentage of EV registrations in total new passenger vehicle registrations. The registration number of total new passenger vehicles is the sum of registrations for new EVs and new internal combustion engine vehicles. Measured by city and month. Source: Huaguanyun automobile big data platform.

Table A1 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) New EV registrations (domestically-produced)	1								
(2) Purchase subsidy per vehicle	0.019***	1							
(3) Vehicle replacement subsidy per vehicle	–0.002	0.112***	1						
(4) Charging subsidy per vehicle	0.018***	–0.004	0.014***	1					
(5) Charging discount	0.039***	–0.012***	0.052***	0.130***	1				
(6) Driving restriction exemption	0.040***	0.046***	–0.016***	0.141***	0.051***	1			
(7) Parking fee benefits	0.006**	0.043***	–0.026***	0.101***	–0.006*	0.117***	1		
(8) Toll exemption	0.053***	–0.023***	–0.015***	–0.012***	0.072***	0.027***	0.362***	1	
(9) Per-vehicle NEV credits	0.022***	–0.424***	–0.044***	0.009***	0.041***	0.019***	0.037***	0.027***	1

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1.

Table A2 Results using GMM estimations

Dependent variable: New domestically-produced EV registrations$_{r,i,t}$				
	Internal instruments only		External instrument also	
GMM specification	Difference	System	Difference	System
	(1)	(2)	(3)	(4)
New domestically-produced EV registrations$_{r,i,t-1}$	0.300***	0.385***	0.299***	0.383***
	(0.057)	(0.045)	(0.057)	(0.046)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t}$	0.004	0.270***	0.004	0.232***
	(0.107)	(0.080)	(0.107)	(0.077)
Number of instruments	113	116	113	117
Other incentives control	Yes	Yes	Yes	Yes
Range fixed effects	No	No	No	No
City fixed effects	No	No	No	No
Month-of-year fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	101,120	106,176	101,120	106,176

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Robust standard errors are shown in parentheses and are clustered at the city-range level.

Table A3 Bound estimates for domestically-produced EVs, LR estimator, monthly data

Dependent variable: New domestically-produced EV registrations$_{r,i,t/i,t}$				
	Three-dimensional (range-city-month)		Two-dimensional (city-month)	
	Controlled effect $\hat{\beta}$	Identified set $[\hat{\beta}, \beta^*(Min\{1, 1.3\hat{R}^2\}, \delta = 1]$	Controlled effect $\hat{\beta}$	Identified set $[\hat{\beta}, \beta^*(Min\{1, 1.3\hat{R}^2\}, \delta = 1]$
	(1)	(2)	(3)	(4)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t/i,t}$	0.348***	[0.348, 4.574]	7.061***	[7.061, 138.760]

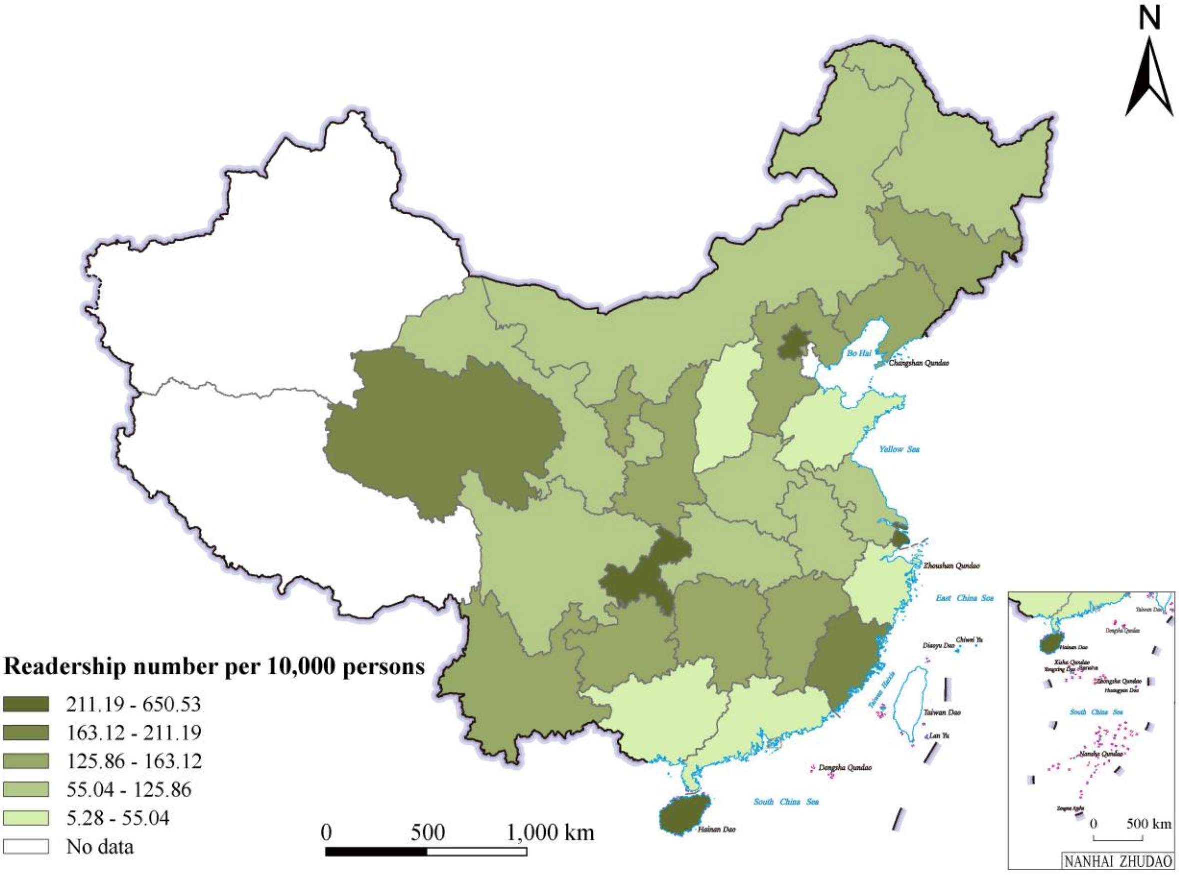
Notes: *** p<0.01. ** p<0.05. *p<0.1. The results in columns 1 and 3 are from columns 1 and 7 of Table 4. The result in column 2 is calculated using Stata code *psacalc2* and the result in column 4 is calculated using Stata code *psacalc* from Oster (2019).

Table A4 Distributed lagged results for domestically-produced EVs, NB estimator, monthly data

Dependent variable: New domestically-produced EV registrations$_{r,i,t}$			
	(1)	(2)	(3)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t}$	0.063***	0.067***	0.069***
	(0.007)	(0.008)	(0.008)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t-1}$	0.007**	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t-2}$		–0.003	–0.011***
		(0.003)	(0.002)
Purchase subsidy per vehicle ('000 CNY, real)$_{r,i,t-3}$			0.011***
			(0.003)
Vehicle replacement subsidy per vehicle (CNY, real)$_{r,i,t}$	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Charging subsidy per vehicle (CNY, real)$_{i,t}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Charging discount (binary)$_{i,t}$	0.455	0.475	0.500
	(0.646)	(0.643)	(0.636)
Driving restriction exemption (binary)$_{i,t}$	–0.081	–0.060	–0.074
	(0.402)	(0.402)	(0.400)
Parking fee benefits (binary)$_{i,t}$	–0.480	–0.584	–0.623
	(0.537)	(0.548)	(0.554)
Toll exemption (binary)$_{i,t}$	–0.688	–0.777	–0.777
	(0.941)	(0.961)	(1.007)
Per-vehicle NEV credits$_{r,t}$	2.901***	2.892***	2.820***
	(0.330)	(0.333)	(0.335)
Range fixed effects	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Month-of-year fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	118,816	116,288	113,760
Sum of coefficients on Purchase subsidy per vehicle ('000 CNY, real)	0.070***	0.073***	0.078***

Notes: Coefficients for constants are not reported. *** p<0.01. ** p<0.05. *p<0.1. Robust standard errors are shown in parentheses and are clustered at the city-range level. The sample size reduces when adding each additional lag.

Figure A1 Readership of subsidy posts per 10,000 persons by province



Notes: Measured using the cumulative readership of all subsidy posts for each province as of the access date, 11am 15 April 2021.