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The Role of Government in the Market for Electric Vehicles

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Shanjun Li
Xianglei Zhu
Yiding Ma
Fan Zhang
Hui Zhou

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Abstract

To promote the development and diffusion of electric vehicles, central and local governments in many countries have adopted various incentive programs. This study examines the policy and market drivers behind the rapid development of the electric vehicle market in China, by far the largest one in the world. The analysis is based on the most comprehensive data on electric vehicle sales, local and central government incentive programs, and charging stations in 150 cities from 2015 to 2018. The study addresses the potential endogeneity of key variables, such as local policies and charging infrastructure, using the border regression design and instrumental variable method. The analysis shows that central and local subsidies accounted for over half of the electric vehicles sold during the data period. Investment in charging infrastructure is much more cost-effective than consumer purchase subsidies. In addition, the policy that merely provided electric vehicles a distinctively license plate was strikingly effective. These findings demonstrate the varying efficacy across policy instruments and highlight the critical role of government in promoting fuel-saving technologies.

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The Role of Government in the Market for Electric Vehicles: Evidence from China

Shanjun Li   Xianglei Zhu   Yiding Ma   Fan Zhang   Hui Zhou*

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*Shanjun Li is a Professor at the Dyson School of Applied Economics and Management, Cornell University and NBER, sl2448@cornell.edu; Xianglei Zhu is the Chief Data Scientist at China Automotive Technology and Research Center, zhuxianglei@catarc.ac.cn; Yiding Ma is a PhD student at the Dyson School of Applied Economics and Management, Cornell University, ym269@cornell.edu; Fan Zhang is a senior economist at the Chief Economist's Office of Infrastructure, World Bank, fzhang1@worldbank.org; Hui Zhou is a PhD student at the Dyson School of Applied Economics and Management, Cornell University, hz423@cornell.edu. We thank Kyuk-soo Kwon, Yikuan Ji, Bingyang Li, Jinge Li, Chunhui Liu, Youming Liu, Shaochao Ma, and Tianli Xia for excellent data and research assistance.

1 Introduction

The study presents a comprehensive empirical analysis on various driving forces with a focus on the role of government behind the rapid growth of the electric vehicle (EV) market in China based on the most detailed data ever complied on this important market. An electrified transportation system together with a clean electricity grid holds the promise to reduce fossil fuel usage, local pollution, and greenhouse gas emissions (GHGs). In contrast to internal combustion engine vehicles (ICEVs), plug-in electric vehicles (EVs) power the motor using electricity generated from power plants and stored in rechargeable batteries. When operated in all-electric mode, EVs consume no gasoline and produce zero tailpipe emissions. The stored electricity is generated from fossil fuels or renewable sources. Fossil-fuel power plants produce air pollution but have much better fuel efficiency than internal combustion engines.

The introduction of Nissan Leaf and Chevrolet Volt in 2010 marked the beginning of the mass market for EVs.[1] The United States had an early start in the EV market but the market in China grew rapidly to become by far the largest one by volume in 2015 as shown in Figure 1. After a decade of market development, new passenger EV sales, including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), reached 2.2 million units globally in 2019, accounting for about 2.5% of total new passenger vehicles sales. The largest two EV markets, China and the United States, contributed to 50% (1.1 million) and 15% (0.33 million) of all passenger EVs sold. In terms of the share of EVs in the new vehicle market, Norway has by far the world's highest share at 55.9%, compared with Sweden at 11%, China at 4.7%, and the United States at 1.9%.[2] [3]

The transition from ICEVs to EVs is challenging due to various economic and technological reasons including the high upfront purchase cost mainly due to the high cost of batteries, the limited driving range and the need for charging infrastructure, and inherent and perceived

[1]Tesla Motors was instrumental in the come-back of EVs by introducing Tesla Roadster, an all-electric sport car in 2006 and beginning general production in March 2008. But the model with a price tag of over $120,000 was out of the price range of average buyers. When first introduced in the US market in December 2010, Nissan Leaf had a price tag of $33,000 and Chevrolet Volt $41,000.

[2]Sources: https://www.marklines.com and https://insideevs.com/.

[3]In China, electric two-wheelers, including electric bikes and electric motorcycles – is another type of alternative fuel vehicle, that has experienced explosive growth over the past few decades. Sales of electric two-wheelers started in 1999 and started to take off in 2004 when 40,000 were sold. Since then, more than 20 million are sold each year and there are now over 300 million motorized two-wheelers on the road. Electric two-wheelers provide a low-cost low-emission mobility that fills an important niche in China's transportation system. However, because government regulation and incentive policies for the adoption of electric two-wheelers are completely different from those for EVs, it is beyond the scope of this paper to analyze the growth of electric two-wheelers in China.

uncertainty about the quality of this new technology. Nevertheless, the transition presents a tremendous market opportunity for firms and governments. To get ahead of the curve, central and local governments in major countries have developed ambitious goals of EV adoption and implemented various policies to promote the technology.[4] These policies included subsidies for EV buyers to reduce the upfront purchase cost in the form of tax credits or rebates, subsidies for charging stations to reduce the installation cost, and a range of non-financial policies such as subsidized electricity for charging, parking privileges, and road usage privileges. In addition to these policies aimed at the demand side, there are supply-side policies such as the EV mandate that requires automakers to meet a target of EV share in their new vehicle fleet and fuel economy standards that target the average fuel economy of the new fleet by automaker.

Government intervention could be justified from multiple market failures that may exist in the EV market and could lead to socially inefficient adoption of EVs. These market failures include consumer mis-perception or imperfect information on product attributes (e.g., quality or fuel-cost savings), inadequate pricing of externalities (local air pollution and GHGs) from automobile gasoline usage, and spillovers such as indirect network effects in the demand side and technology spillovers among automakers. We discuss these issues in greater detail in Section 2.2. While the optimal policy to address each market failure might be different, consumer subsidies have been the most commonly used strategy likely due to their administrative convenience and political attractiveness. Understanding the impacts and cost-effectiveness of consumer subsidies and other policies is critical in designing policies to promote the technology.

The objective of this study is to provide to our knowledge the first empirical analysis on various policy- and market-drivers of the rapid development of China's EV market. Understanding the role of these drivers is important for at least two reasons. First, China is by far the world's largest energy consumer and automobile market with nearly 26 million units in 2019, compared to 17 million in the United States. Due to the unprecedented growth of vehicle ownership and driving demand, China accounted for nearly 50% of the increase in world's oil consumption during the last two decades. The transition from ICEVs to EVs in China therefore could have important implications for the world's oil and energy markets, and global GHG emissions. Second, all the major international automakers have production facilities

[4] In the 2011 State of the Union address, President Obama set up a goal of having one million EVs on the road by 2015 but the goal was only met by 40%. The Chinese government set up a goal of half a million EVs on the road by 2015 and five million by 2020. Although it badly missed the first goal due to a slow start, China is well on its way to meet the second goal. The German government developed an initiative to reach one million EVs by 2020 but it is unlikely that it can reach 40% of that goal. Sources: https://www.ev-volumes.com/datacenter/ and https://wattev2buy.com/global-ev-sales/.

in China in the form of joint ventures (JVs) partnered with domestic automakers.[5] JVs take up about two-thirds of the market and dominate the luxury segment while imports account for only about 5 percent of the market. The size of the EV market could benefit the global trend of transportation electrification by offering a fertile trial ground of new technologies and reducing the cost of batteries, the cost component critical to the transition from ICEVs to EVs.

To quantify the impacts and cost-effectiveness of different driving forces on consumer EV demand, we have compiled to our knowledge the most comprehensive data on China's EV market including quarterly EV sales by vehicle trim by city from 2015 to 2018, vehicle attributes by trim, information on battery suppliers, detailed information on public charging stations, consumer subsidies and other policies aimed at promoting consumer adoption of EVs from central and local governments, and social and economic variables at the city level. We use a linear regression framework to estimate EV demand among individual/household buyers with a focus on consumer price response, non-financial policies, and charging infrastructure availability.[6]

There are three key identification challenges. First, the price variable, crucial to estimating consumer response to subsidies, could be endogenous due to unobserved product attributes, i.e., attributes that consumers value but are unobserved in the data (e.g., product quality and safety performance). As documented in previous studies, unobserved product attributes tend to bias the price coefficient estimates toward zero in demand estimation (Berry et al., 1995), leading to under-estimation of consumer response to consumer subsidies. The second challenge is unobserved demand shocks that could be correlated with government policies (subsidies and other policies) and at the same time affect consumer EV demand. For example, if central and local governments design policies as a response to negative demand shocks, we would under-estimate the effectiveness of the policies. The third challenge is due to the simultaneity between consumer EV demand and charging station investment, which could render the charging infrastructure variable endogenous. The simultaneity arises because of the fact that the EV market can be characterized as a two-sided market (EVs and charging stations) with indirect network effects. The decision of consumer adoption depends on the size of charging infrastructure and the decision

[5] The joint-venture requirement for foreign automakers is part of the long-term "technology-for-market" strategy by the Chinese government. Amid the recent trade war between China and the United States, the Chinese government has promised to lift the requirement for the auto industry from 2021. With a special permission, Tesla built its fully owned gigafactory in Shanghai with a capacity of 250,000 units per year and it has started to produce Model 3 in December 2019.

[6] Individual buyers account for about 65% of total EV sales during our data period. Institutional buyers (e.g., government agencies, companies and taxi fleets) are subject to different subsidy policies and their decision making process could be subject to different considerations.

of investing in charging stations hinges on the size of the installed base of EVs.

We address the three identification challenges using two strategies. The first one is the instrumental variable (IV) method while the second one is a city-border regression design. Our preferred specification implements these two strategies in the same linear regression framework. First, we instrument the price variable using central subsidies and battery capacity (kWh). The central subsidies follow a step function of vehicle driving range. By including driving range in the demand equation, the identification leverages the discrete nature of the subsidies around the cutoffs. The identification assumption is that unobserved product attributes are unlikely to have discrete jumps around the driving range cutoffs. The second IV for price is battery capacity: it should affect vehicle prices as the battery is an important cost component and its cost depends on the capacity. The identification assumption is that battery capacity is not correlated with unobserved product attributes. Firm choices of battery capacity are likely dictated by the decisions on vehicle driving range and weight, which we control in our regressions.

Second, we instrument for the charging infrastructure variable using the installed EV base by institutional buyers (lagged one period). The institutional EV stock likely affects investors' decision to build charging stations. The identification assumption is that the lagged institutional EV stock is unlikely to be correlated with concurrent demand shocks to individual buyers. Lastly, we use a city-border regression design to address potential endogeneity in policy variables due to unobserved local demand shocks. The design exploits the fact that local policies change sharply across city borders, but unobserved demand shocks such as changes in transportation costs, access to dealer stores, and consumer preference are likely to be similar among neighboring cities. In practice, we group neighboring cities into clusters, and then include cluster-time fixed effects to control for time-varying local unobservables common in the same cluster, as well as cluster-brand-year fixed effects to control for demand shocks that are specific to each brand in a cluster.

Based on the regression results, we conduct simulations to examine the effects of each policy and non-policy drivers and compare the cost-effectiveness of different policies. Our analysis provides the following three key findings that are robust across various specifications and sample cuts. First, generous consumer subsidies from central and local governments (about 26% of pre-subsidy vehicle prices) played a crucial role in the rapid growth of the market by explaining over half of the EVs sold during our data period. The impact is similar in magnitude to that of the subsidy programs in the United States and Norway in Li et al. (2017) and Springel (2019). Second, there are significant indirect network effects from charging infrastructure on EV demand.

Compared with consumer subsidies, investment in charging infrastructure is about four times as cost-effective in promoting EV sales. Both Li et al. (2017) and Springel (2019) show the same qualitative finding but the advantage of charging infrastructure investment in cost-effectiveness is twice as strong in China as found in those studies. Third and perhaps most striking, the policy which merely grants EVs a distinctive looking license plate in green is very effective, increasing EV sales by 18%. This large impact could be driven by conspicuous conservation whereby consumers seek status through signaling their environmental friendliness (Sexton and Sexton, 2014). It could also be due to increased salience of EVs as consumer choices or perceived endorsement of product quality brought about this policy change (Chetty et al., 2009; Busse et al., 2015). These findings have important implications for the design of EV policies in China and other countries.

We organize the rest of the paper as follows. Section 2 discusses the industry background, policies, and data. Section 3 presents the empirical model and identification challenges. Section 4 discusses the estimation results and robustness checks. In Section 5, we present the counterfactual simulations to evaluate the role of different drivers of consumer demand. Section 6 concludes.

2 Industry Background and Data Description

2.1 Industry Background

Electric vehicles are capable of running on electricity generated from outside sources. There are two types of EVs on the market: battery electric vehicles (BEVs) which run exclusively on high-capacity batteries (e.g., Nissan LEAF), and plug-in hybrid vehicles (PHEVs) which use batteries to power an electric motor and use another fuel (gasoline) to power a combustion engine (e.g., Chevrolet Volt). EVs have the potential for reducing energy usage and emissions because of the efficiency gain from switching from ICEs to large power plants: the fuel efficiency (converting source to usable energy) is about 30%-40% from ICEs but it could reach over 50% for coal plants or even 90% for hydro plants. The benefit could be even higher if the electricity is from renewables.[7]

Since the introduction of Chevrolet Volt and Nissan Leaf as the first mass-market models into the US in late 2010, worldwide EV sales have grown to about 2.5% (or 2.2 million units) of the

[7]Apart from environmental benefits, whether EV adoption could lead to unintended consequences on other emblematic transport externalities such as congestion and safety receives less attention. Some evidence suggests that EV adoption could increase pedestrian traffic safety risk (Karaaslan et al., 2018).

new vehicle market in 2019. Figure 1 shows EV sales and the number of charging ports/outlets in China, US, and Europe. China is the largest EV market with the most charging stations. The ratio of charging stations per EV sold is the highest in EU at about 6:1, relative to 4:1 in China and US.

Figure 2 shows the number of EV automakers and EV models in China and US. There are 66 EV automakers and 195 models in 2019 in China, compared to about 23 firms and 45 models in the US. As shown in Figure 3, the US EV market is quite concentrated with the top 5 firms accounted for over 80% of the EV market in 2018 with Tesla taking up 50% of the EV market. In China, the top 5 firms account for less than 60% of the market in 2018. The largest EV producer in China, BYD, has a market share of about 20% and followed closely by Beijing Automotive Group.

China's central government has developed ambitious short- and long-term goals to develop the EV industry and improve overall fleet fuel economy. The implicit goal is to reach annual sales of two million EVs in 2020 (about 8 percent of new vehicles sales), seven million (or 20%) in 2025, and 15 million (or 40%) by 2030. The fuel economy standards require automakers to reach 5 liter/100km (or 47 miles per gallon) among their new vehicle fleet in 2020, 4 liter/100 (or 59 miles per gallon), and 3.2 liter/100km (or 74 miles per gallon) by 2030.[8] These ambitious fuel economy targets necessitate a dramatic increase of EVs in the vehicle fleet.

2.2 Government Policies

The auto industry has long been considered as a strategic/pillar industry by central, provincial, and local governments due to its large impacts on employment, local GDP and upstream industries (such as auto parts, iron and steel). Governments at various levels have implemented many policies to promote the industry (Barwick et al., 2017; Bai et al., 2020). In the face of increasing energy and environmental pressure, governments make strategic development plans to prioritize the development of the EV industry. EV polices have been implemented not only to promote the adoption of EVs but also to push the upgrading of the auto industry in China and to build advantage in the international market.

[8]The US fuel economy standard was previously set to reach 55 miles per gallon under the rules promulgated under the Obama administration. As a major department, the Trump administration rolled back the standard and the new rule would require automakers to achieve an average fuel economy of 40 miles per gallon by 2026.

2.2.1 Policy Rationales

There are several rationales behind the government intervention and these rationales stem from market failures in this market. First, gasoline usage from ICEVs generate local air pollutants and GHGs that are not adequately reflected in gasoline taxes (Parry and Small, 2005; Parry et al., 2014). Compared to ICEVs, EVs are cleaner when the electricity comes from clean generation such as natural gas and especially renewables. In regions that depend heavily on coal or oil for electricity generation, EVs may not demonstrate an environmental advantage over gasoline vehicles (Holland et al., 2016). Nevertheless, the electricity grid continues to become cleaner around the world due to the adoption of abatement technologies, the switch from coal to natural gas, and the deployment of renewable generation. In addition, emerging technologies are being developed to better integrate EVs and renewable electricity generation. The integration of the intermittent energy source such as solar and wind with EV charging can not only help realize EV's environmental benefits but also address the issue of intermittency and serve as an energy buffer by systematically leveraging EV batteries' storage capability (Lund and Kempton, 2008).

Second, consumers may mis-perceive product quality or future operating costs due to imperfect information about the new technology or miscalculation/inattention of future fuel savings (Allcott, 2013). Firms may not be able to appropriate the full benefit of information provision due to for example information spillovers, leading to the underprovision of information and inefficiency in the market (Stigler, 1961; Hirshleifer, 1971). In addition, for energy-consuming durables such as vehicles, consumers need to factor into future operating costs into the consideration in comparing different options. Mis-calculation or mis-perception could occur in understanding the trade-off between the high upfront purchase cost and future fuel savings for new energy efficient technologies, leading to socially inefficient adoption of these technologies (Jaffe and Stavins, 1999).

Third, there could be spillovers in both the demand and supply sides of the market that could lead to inefficient adoption of EVs. On the demand side, the EV market can be characterized as a two-sided market (EVs and charging stations) with indirect network effects, which has been empirically documented by previous research (Li et al., 2017; Zhou and Li, 2018; Springel, 2019). The decision of consumer adoption depends on the size of charging infrastructure and the decision of investing in charging station hinges on the size of installed base of EVs. This type of spillovers represents a source of market failure since the marginal consumer/investor only consider the private benefit in their decision and the network size on both sides is less than optimal (Liebowitz and Margolis, 1995; Church et al., 2002).[9] On the supply side, there could be positive technology spillovers among firms especially in the early stage of new technology diffusion (Stoneman and Diederen, 1994). The development of EV technology requires significant investment but the technology know-how once developed can spread through many channels including worker mobility and the supplier network (Kim and Marschke, 2005; Blalock and Gertler, 2008; Poole, 2013; Serafinelli, 2019). So the private returns of R&D are likely smaller than the social returns, leading to under-investment in the market.

2.2.2 Financial Incentives

Consumer subsidy is the most common policy to promote EV adoption across countries. As a comparison, Table 1 presents the level of subsidies and eligibility rules in US and China. Effective from 2010, US federal government provides a federal income tax credit to new EV buyers based on each vehicle's battery capacity and the gross vehicle weight rating, with the amount ranging from $2,500 to $7,500, with a phase-out target of 200,000 EVs sold. In addition to the federal level mandate, according to the National Conference of State Legislatures, as of 2017, 46 out of 50 states have published incentives (monetary and non-monetary) to promote the adoption of EVs.[10] These incentives include tax exemptions and rebates for EVs and non-financial incentives such as high-occupancy vehicle (HOV) lane access, toll reduction, and free parking. In addition, federal, state, and local governments also provide funding to support charging station deployment (Li et al., 2017; Li, 2020).

Similarly, Chinese government institutes the policy plan promoting EV adoption at both central and local levels, with the main device being consumer subsidy contingent on vehicle quality attributes. The central subsidy program experienced considerable coverage expansion starting from 2009 with updates in every 3 to 5 years. The policy program followed a phase-out design over each of the effective policy period. Local subsidies are generally pegged to the central subsidy amount by a certain ratio depending on the respective government mandate at the provincial and city levels, some with additional restrictions contingent on various vehicle

[9] Given the nature of the market, each side of the market is unlikely to internalize the external effect on the other side through market transactions. If EVs are produced by one automaker, the automaker would have incentive to offer a charging station network to increase EV adoption. Nissan and GM are the two early producers of EVs but more and more auto makers are entering the competition. Nissan is a large owner of charging stations but GM is not. Tesla is building its own proprietary network for Telsa owners only. This suggests that they recognize the importance of charging stations in EV adoption but this would create duplicate systems.

[10] Source:
https://www.ncsl.org/research/energy/state-electric-vehicle-incentives-state-chart.aspx

attributes. Figure 5 shows the per vehicle average consumer subsidies (including central and local subsidies) across the 150 cities in 2015 and 2018. In 2015, subsidies were available for only major cities and at a higher amount. In 2018, the coverage expanded as central subsidy was made available for all cities and the amount decreased in general.

Central Policies In 2009, Chinese government first initiated the federal level EV policy through a pilot program named "Ten Cities, Thousand Cars" jointly announced by the Ministry of Finance (MoF), Ministry of Science and Technology (MoST), Ministry of Industry and Information Technology (MIIT) and National Development and Reform Commission (NDRC). The experimental program issued central subsidy upon EV purchases. It was promoted first in the public sector and expanded to the private sectors in 2010.[11] The program started from five pilot cities and rolled out in three waves, with total enrollment of 25 cities.[12]

Following this first wave of pilot program, Chinese central government continued to expand the policy coverage and devised a set of specific subsidy programs contingent on the MIIT vehicle eligibility catalog and changed the technical specification measure to driving range of the vehicle. According to the September 2013 policy document "On Continuing Promotion and Application of New Energy Vehicles" published by the four central ministries, central subsidy should be distributed based on three tiers of driving ranges for BEVs (one tier for PHEV at 50km), and eligible vehicles could get from ¥35,000 to ¥60,000 depending on the driving range. The amount of subsidy issued to private passenger vehicles should be reduced by 10% and 20% respectively in 2014 and 2015. In 2014, the four ministries revised the subsidy reduction ratio to 5% and 10% respectively, providing further financial incentive for consumers.[13] Henceforth, central subsidy policies are developed based on similar scheme, the issuance of which depends on driving range and vehicle fuel type with a phase-out design, as shown in Table 2. The policy program was instituted in two waves and eventually covered 39 regions of 88 pilot cities, the scale of which increased by over threefold compared to the first wave of the pilot program.[14]

In April 2015, the four central ministries published the "Announcement of Financial Policies

[11]Subsidies for private EV purchases were granted later in May 31, 2010. Source: http://miit.gov.cn/n1146295/n1652858/n1652930/n3757018/c3757144/content.html

[12]The five cities are Shanghai, Changchun, Shenzhen, Hangzhou and Hefei according to the policy appendix, with one additional city Beijing ("5+1" plan). The pilot cities increased to 25 later in 2011. Source: https://www.tyncar.com/zhengce/xnyqcsdcs.html

[13]The four central ministries announced the revised reduction ratios in February 2014. Source: http://www.gov.cn/gzdt/2014-02/08/content_2581804.htm

[14]Source: https://auto.qq.com/a/20160121/020348.htm

on Promoting New Energy Vehicles", laying out the policy plan from 2016 to 2020.[15] Specifically, the magnitude of subsidy will be further reduced by 20% in 2017-2018 and by 40% in 2019-2020 based on the standard of 2016. The minimum threshold for driving range was raised to 100km for BEVs and to 50km and 70km for PHEVs by different regulatory standards. The policy also revised driving range cutoffs, with the corresponding subsidy ranging from ¥25,000 to ¥55,000. It also imposed additional technical specifications on the maximum speed for BEVs and fuel consumption for PHEVs.

On the basis of previous policies, the central government published two revisions in 2018 and 2019, respectively. In February 2018, the central government published a revision towards the previous five-year policy plan. The revision defined a more detailed subsidy schedule by driving range cutoffs for BEVs. The minimum eligible driving range was raised to 150km, and the maximum threshold to 400km. The revision specified additional requirement on minimum battery density at 105Wh/kg. Given the same driving range, models with higher battery density could get more subsidy and the lower ones get less. Furthermore, the revision required minimum energy efficiency in kWh/100km (as a function of weight) to pass certain threshold, and the more efficient models are eligible for higher subsidies.[16]

The revision in March 2019 updated the minimum eligible driving range to 250km. BEVs with driving range between 250km and 400km are eligible for central subsidy of ¥18,000, and BEVs with driving range above 400km are eligible for ¥25,000. PHEVs get ¥10,000 of central subsidy with driving range greater than 50km. The driving range threshold for eligible BEVs became more stringent and the subsidy amounts are cut by over 50%. The revision also required local governments to terminate subsidy by June 26, 2019.[17] After the reduction and cancellation of subsidies, EV sales experienced negative growth for six consecutive months in 2019. Due to the negative sales impact of the subsidy removal and the ongoing pandemic, the four ministries (MoF, MoST, MIIT, and NDRC) issued a policy in April 2020 to reinstate the subsidy policy with a gradual reduction by 10%, 20%, and 30% during 2020-2022, relative to 2019 levels.[18]

[15]Source: http://fgk.mof.gov.cn/law/getOneLawInfoAction.do?law_id=83837

[16]The four central ministries announced the revision in Februrary 2018. Source: http://www.miit.gov.cn/n1146285/n1146352/n3054355/n3057585/n3057592/c6064667/content.html

[17]The policy was announced in March with a three-month transition period. Vehicles sold during the transition period that do not meet the 2019 revised standard were only eligible for 0.1 of the 2018-level central subsidy. Source: http://www.gov.cn/xinwen/2019-03/27/content_5377123.htm

[18]Source: http://www.gov.cn/zhengce/zhengceku/2020-04/23/content_5505502.htm

Local Policies EV subsidies at the local level follow closely the central guidelines, with variations depending on additional restrictions issued by local governments. The subsidy amount is generally pegged to the amount of central subsidy, which could be a 1:1 match or of certain ratio. Hence, the phase-out timeline and eligibility conditions of central subsidy also affect local subsidy programs. In general, cities issue subsidies following the catalog of eligible vehicle models provided by MIIT, but there exist exceptions in which cities publish additional requirements such as vehicle quality attributes to further regulate the issuance of subsidy at local level. For example, Beijing and Shanghai distribute local subsidy based on own list of eligible vehicles.[19] Heifei set its minimum driving range threshold for eligible BEVs at 150km in 2013, while the central subsidy minimum threshold was at 80km.[20] Hangzhou issued subsidy based on vehicle size starting from 2017.[21] When issuing subsidy proportionate to central subsidies, local financial incentives are generally sponsored by both provincial and city governments with different percentages of contribution (e.g. provincial government provides 70% and city government provides 30%). Under the same provincial mandate, cities could implement different local incentives as well. Major cities such as province capitals and pilot cities that were enrolled in EV policy programs at earlier stage tend to have more complicated policy design with higher subsidy amount, while other cities rely more heavily on central and provincial guidelines. Other miscellaneous financial incentives such as electricity fee subsidy, parking fee reduction, switch subsidy and insurance subsidy are often designed and implemented at the local level.

2.2.3 Non-financial Incentives

Non-financial incentives play an important role in promoting electric vehicle adoption, many of which were proven to be effective in boosting EV adoption. A vehicle registration privilege was granted to electric vehicles in cities such as Shanghai, Beijing, Tianjin, Guangzhou, Hangzhou and Shenzhen, in which vehicle purchase was subject to a certain quota and license plates were issued through an auction or a lottery. In some cities, electric vehicles are not subject to road access restriction designed to alleviate traffic congestion and pollution issues. In 2015, only seven cities had driving restriction exemptions rules for EV. In 2018, the number reached 29. Another major non-financial policy program is the green plate policy, which provides special plates for electric

[19] Policy for Beijing: http://czj.beijing.gov.cn/zwxx/tztg/t20180130_883639.html
Policy for Shanghai: http://www.shanghai.gov.cn/shanghai/download/gongkai/hfbf1421.pdf

[20] Policy for Hefei: http://www.caam.org.cn/chn/9/cate_104/con_5197593.html

[21] Policy for Hangzhou: http://www.hangzhou.gov.cn/art/2017/8/14/art_1302334_4131.html

vehicles that are distinguishable from the ICE models. In addition to displaying the conspicuous adoption of energy-efficient vehicles, the green plate also helps make EVs easily recognizable for relevant road traffic and parking infrastructure privileges. The policy was promoted through three waves starting from December 2016. The enrollment was restricted to five pilot cities in 2016. The coverage expanded further in 2017 to 20 cities and was implemented at national scale by the end of 2018 (effectively 147 cities in our sample) as shown in Figure 6.

In addition to the incentives above that explicitly target the demand side, the central government also issued policy plans to address energy efficiency in production activities. In September 2017, MIIT issued the mandate on new energy vehicles using dual credit point system for both corporate average fuel consumption (CAFC) for ICE models and new energy vehicles (NEVs), which could be considered as a modified version of California's Zero Emission Vehicle (ZEV) mandate.[22] As an addition to the existing regulation on fuel consumption of ICE models, NEV production and importation will result in credits accumulation for the corresponding manufacturers. Manufacturers with production and import volume more than 30,000 are subject to the dual credit point system, and the credit proportion for NEVs are set at 10% and 12% for 2019 and 2020 respectively. The mandate is considered as a continuation of the subsidy policies with less financial investment from the government, and the incentives are injected through the supply channel instead.

2.3 Data Description

Vehicle data We obtain EVs sales at the city-quarter-trim level from 2015 to 2018. Our sample of analysis has 150 cities. This list of cities includes (1) the top 40 cities with the largest aggregate EV sales during our data period, and (2) their neighboring cities in order to conduct city-border analysis. In 2018, the total sale of passenger EVs in these 150 sample cities were 0.82 million, accounting for 78% of the national EV sales.[23] Our analysis focused on sales to individual buyers (rather than institutions) because institutional purchases (e.g., by government agencies and rental companies) are subject to different subsidy policies and face different incentives from individual purchases. In the 150 sample cities, individual sales accounted for about 65% of total EV sales in 2018.

[22] Official document of full description on the mandate issued by the five central ministries: http://www.gov.cn/xinwen/2017-09/28/content_5228217.htm

[23] Among the EV sales, BEVs took up 76% with PHEV being the rest. The EV sales in the top 40 cities accounted for 69% of national EV sales while the 110 other cities in the sample accounted only 9%.

We have detailed vehicle attributes at the trim level. A vehicle trim is defined as a unique combination of brand (e.g., Toyota), model (e.g., Camry), fuel-type (e.g., BEV or PHEV), and driving range. After dropping very unpopular models with annual national sales less than 400, there are 27,577 observations with 190 unique trims from 44 firms in our data. Figure 7 presents annual new EV sales (individual purchases) per million residents by city in 2015 and 2018. There are two salient features. First, sales increased dramatically from an average of 67 per million residents to 497 during 2015-2018. Second, there is large spatial heterogeneity: the highest and lowest sales per million residents were 5,587 and 7 in Shenzhen, Guangdong Province and Hechi, Guangxi Autonomous Region, respectively in 2018. Interestingly, many neighboring cities with similar household income levels have very different level of EV penetration, likely due to differences in local policies.

Charging Stations We obtain information on non-private charging stations from China Electric Vehicle Charging Infrastructure Promotion Alliance, a member organization of charging operators. Our data contain information on opening data, location, ownership type (public or dedicated), the number of charging ports/outlets (by AC or DC) on site. Public charging stations are open to all while dedicated are open to a designated group such as residents in a community or company employees. There are about 337,000 (non-private) charging ports/outlets operated by their members, accounting for 69% of all operating charging ports at the end of 2019 in China.[24] Figure 8 shows the number of charging ports per million residents for the 150 sample cities at the end of 2015 and 2018. The average number of charging station per million residents across cities increased from 4.7 to 134 from December 2015 to December 2018. The overall temporal and spatial patterns are very similar to those of EV sales in Figure 7. The correlation coefficient between EV sales and the number of charging ports per million residents is 0.46 and 0.79 for the 150 cities in 2015 and 2018, respectively.

Policies We are not aware of a centralized database on various EV policies in China. We collect the central and local policies from a variety of online sources including government websites, industry reports, and newspapers. Central subsidy programs are issued through official government documents that are generally published on the government official websites of the Ministry of Finance (MoF), Ministry of Science and Technology (MoST), Ministry of Industry and Information Technology (MIIT) and National Development and Reform Commission

[24]Among these charging ports, 71% are open to the public and the rest are dedicated to groups.

(NDRC). Local subsidy policies are issued by provincial and city governments and could be retrieved from official documents released on government websites and unofficial online documentation sources such as news articles. The non-financial incentives such as exemption from driving restrictions and green plate policy are mostly announced separately from the subsidy programs. We collected these incentives through various sources including official government document releases, news and industry reports. The official policy documents and most news reports contain general information of the policy, amount of subsidy, eligibility conditions (e.g. vehicle attributes requirements) and the effective policy period. This allows us to match the policy directly to vehicle models over a certain time period based on the eligibility conditions.

Noticeably, the release date of the official documents is mostly later than the effective policy start date, causing subsidy issuance to be retroactive. However, in practice, consumers are supposed to have access to the post-subsidy price under the contemporaneous subsidy scheme. At the central level, according to the official document on subsidy issuance released by the four ministries, automobile manufacturers shall charge consumers the post-subsidy price for eligible vehicle purchases; the central government will finalize the settlement for subsidy issuance to auto manufacturers contingent on application approval.[25] According to the public announcements made by the MIIT about subsidy settlement with auto manufacturers in 2018, settlement issuance approval rate is about 94%.[26] Local subsidy issuance and settlement follow similar procedures, in which the consumers pay the post-subsidy price and auto manufacturers apply for reimbursement to local government.[27] Hence, it is fair to assume that despite of the retroactive policy announcements, consumers are still eligible for the appropriate subsidy per the policy implementation mandate. In order to better characterize the issuance of subsidy at different policy phases, we make an assumption on consumers' expectation for policy availability contingent on existing local subsidy programs: if a province or a city had subsidy program in the previous time period, consumers would anticipate the continuation of the subsidy issuance (could

[25] The official documents for 2013-2015 and 2016-2020 both stated that the subsidies should target consumers directly, and consumers are eligible to pay the post-subsidy price. In the policy document for 2013-2015, the government issues quarterly advance payment to manufacturers and conducts final settlement annually. In the policy document for 2016-2020, both the advance payment and settlement are conducted annually. Sources: http://www.gov.cn/zwgk/2013-09/17/content_2490108.htm and http://fgk.mof.gov.cn/law/getOneLawInfoAction.do?law_id=83837

[26] The MIIT publishes the announcement on subsidy settlement by region-firm-vehicle model and shows the number of applications versus application approval. Approval rate is calculated using the data provided in the policy document appendix. The 2018 settlement was published in November 2019. Source: http://www.miit.gov.cn/n1146295/n7281310/c7548610/content.html

[27] Nevertheless, since local subsidy issuance is not uniformly administered as central subsidy, more delays in settlement are observed in practice. Source: http://www.nengyuanjie.net/article/25080.html

be of a different amount) in the next period and benefit from the policy as of its effective start date instead of announcement date. This assumption helps capture the reality by accounting for the advance payment made by auto manufacturers to ensure the proper delivery of subsidy.

Summary Statistics Table 3 presents summary statistics of our full data including vehicle sales, vehicle attributes, and policies. The average Manufacturer Suggested Retail Price (MSRP) is about ¥200,000 (or $30,000) with a range of ¥81,800 to ¥608,800. The 2018 Cadillac CT6, a PHEV, is the most expensive EV model in our data followed by Audi A6 and Volvo XC60, both of which are also PHEV.[28] While these high-end models are produced by JVs or imports, the low-end models are mostly produced by China's domestic automakers such as Kangdi, Dongfeng Xiaokang, and ChangAn. Different from the high-end models, these low-end models are not sold outside China. Consumer prices are MSRPs subtract central and local subsidies, which amounted to be over ¥45,000 per vehicle on average in our sample period. There is significant variation over time and across cities as described in the policy discussion above. In addition, there is also important variation across vehicle models even within a city due to the fact that the amount of subsidy depends on fuel type and vehicle driving range. Our analysis of vehicle demand also controls for a set of vehicle attributes such as vehicle size (the length by width), motor power, vehicle weight, and driving range. Battery capacity and the EV stock by institutional buyers are to be used as instruments in our analysis.

3 Empirical Model and Identification

In this section, we first present our empirical model and then discuss the identification strategy.

3.1 EV Demand

To describe the empirical model for EV demand, we define a vehicle model as brand-model name combination (e.g., BYD Song) and a trim as a unique combination of model and driving range combination (e.g., BYD Song with a range of 80km). Let m index a model, k index an EV trim, c index a city, y index a year, and t index time (i.e., year-quarter). We specify the following

[28]Cadillac CT6 PHEV is produced in the production facility in Shanghai owned by the joint venture (JV) between GM and Shanghai Auto (SAIC). Cadillac is a popular luxury brand among Chinese consumers, which drives the decision to base the production of this model in China.

equation as the starting point of the analysis:

$$ln(q_{ckt}) \quad = \beta_1 p_{ckt} + \beta_2 N_{ct} + \beta_3 DR_{ckt} + \beta_4 GP_{ct} + X'_{ckt}\alpha + \eta_{cm} + \delta_t + \xi_{cy} + \varepsilon_{ckt}, \tag{1}$$

where q_{ckt} is the sales of EV trim k in city c and year-quarter t. p_{ckt} denotes the consumer price (or after-subsidy price) of trim k in city c and year-quarter t. It is defined as the manufacturer's suggested retail price (MSRP) less the related subsidies at both federal and city levels. The coefficient estimate β_1 would allow us to quantify the effect of the subsidies. N_{ct} denotes the total number of public charging ports/outlets that have been built in the city by the end of a given quarter.[29] The coefficient on N_{ct} captures the (indirect) network effect of charging infrastructure on consumer adoption of EVs. DR_{ckt} is an indicator variable being one for trim k if it is exempted from the driving restriction policy. GP_{ct} is an indicator variable being one if city c implements a green plate policy for EVs at time t. X_{ckt} is a vector of vehicle attributes including vehicle size, battery power over weight (a measure of acceleration), and driving range.

We also include a full set of city-model (e.g., BYD Song in Beijing) fixed effects and year-quarter (e.g., the first quarter of 2011) fixed effects in equation (1). City-model fixed effects control for time-invariant product attributes such as quality and brand loyalty that could affect vehicle demand as well as time-invariant local preference for green products (Kahn, 2007; Kahn and Vaughn, 2009) and demand shocks for each model (e.g., a stronger preference or dealer presence for BYD Song in Beijing). Year-quarter fixed effects control for common demand shocks for EVs across cities such as the national change of consumer awareness. In addition, we include city-year fixed effects to control for city-specific demand shocks that vary across years. These could be unobserved local incentives or changes in consumer preference. Since the variation in charging ports is at the city-time (year-quarter) level, including city-time fixed effects would absorb N_{ct}. ε_{ckt} is the unobserved demand shocks for each trim that are time-varying and city-specific (for example, unobserved local incentives that vary across EV trims or city-specific promotions for a vehicle model that vary over time).

Our key parameters of interest are $\beta's$ and they capture the effects of important policy and market drivers. However, each of the corresponding variables is subject to the concern of endogeneity even with the rich set of controls in (1). There are multiple sources of endogeneity. The first source is unobserved product attributes (e.g., quality or prestige) that could render the price variable endogenous. Previous literature on vehicle demand has documented that failing

[29] We use the number of charging ports instead of the total number of charging stations to represent the availability of charging infrastructure but the qualitative findings are the same.

to control for unobserved product attributes could lead to downward bias in the price coefficient estimates (for example Berry et al. (1995) and Petrin (2002)). The city-model fixed effects included in (1) absorbs both observed and unobserved vehicle attributes at the model level that do not vary over time. The remaining variation in price and in observed attributes X_{ckt} comes from the variation across trims within the same model, and more importantly the variation over time for the same trim. Nevertheless, the variation in unobserved attributes across trims within the same model and over time could still be correlated with vehicle price, rendering the price coefficient estimate inconsistent.

The second source of endogeneity is the simultaneous nature between consumer demand for EVs and the investment decision of charging stations. Due to EVs' limited range, the availability of charging facility could help address range anxiety and promote consumer adoption. The importance of charging infrastructure in the early stage of EV diffusion has been shown in Li et al. (2017); Zhou and Li (2018); Springel (2019); Meunier and Ponssard (2020). On the other hand, investors would like to factor into current and future demand conditions into their investment decisions. The simultaneity between consumer demand and fueling infrastructure could result in N_{ct} being endogenous as shown in Corts (2010) and Li et al. (2017) in the context of the US flex-fuel vehicle market and the EV market, respectively.

The third source of endogeneity are unobserved demand shocks or policies that could confound the policies of interest: subsidies, exempt from driving restriction, and the green plate policy. National subsidies vary over time and across vehicle trims based on the driving range. Local subsidies vary over time, across cities and products. The driving restriction and the green plate policies vary over time and across cities due to their staggered rollout. We include time fixed effects to control for common demand shocks at the national level, and city-year fixed effects to control for city-specific demand shocks that vary across years but constant within a year. To the extent that these policies are a response of government to time-varying and city-specific demand shocks, these policy variables would be endogenous. For example, if a city government observes or projects a negative demand shock to its local EV demand, it may start to implement a policy to counteract the negative demand shock. If this is true, the policy impact estimated from OLS would be biased downward.

3.2 Identification Strategy

We address the first two sources of endogeneity, unobserved product attributes and simultaneity using the instrumental variable method. For the third source of endogeneity, we use a city-border regression design to address selection of local policies. To incorporate these identification elements, we use an IV method paired with a city-border design.

To address price endogeneity due to unobserved product attributes, we use two sets of IVs. The first (set of) IV is central subsidy by leveraging the discrete nature of the central subsidy that varies based on driving range cutoffs. In addition, the amount of subsidy changes from year to year as discussed above. The central subsidy offers a valid instrument as it is related to consumer price but unlikely to be correlated with unobserved product attributes for two reasons. First, we use time fixed effects to control for time-varying national common shocks that could be correlated with the year-to-year variation in subsidy. Second, the driving range of the vehicle is included in the regression so the identifying variation in subsidy is due to the discrete nature of the subsidy around the driving range cutoffs. The identifying assumption is that unobserved product attributes are unlikely to change discretely around the driving range cutoffs.

The second set of IVs for consumer price is constructed based on battery capacity (kWh). In particular, we interact battery capacity with supplier dummies. We distinguish battery suppliers as CATL, BYD, and the rest. CATL is by far the largest EV battery supplier in China with a market share of 41.3% and 50.6% in 2018 and 2019 while BYD is the second largest battery supplier with a market share of 20% and 17.3% in 2018 and 2019.[30] Battery is a major cost component for EVs and could account for about 20-60% of vehicle price. The battery cost has decreased dramatically over time with the (volume-weighted) cost reduced from $1,100/kWh in 2010 to less than $160 in 2019 due to technology improvement and the production scale.[31] By the virtue of their production scale and technology capability, CATL and BYD batteries may have cost advantages. The identification assumption is that battery capacity is not correlated with unobserved product attributes. The choice of battery capacity is likely to be dictated by the decisions on vehicle driving range and weight, which we control in our regressions.

To address the endogeneity of the availability of charging infrastructure (i.e., the number of charging ports) due to simultaneity, we use as an IV the lagged stock (i.e., cumulative sales) of EVs purchased by institutions (e.g., government agencies or taxi fleets) during all previous quarters. Our demand analysis focuses on individual purchases, which account for about 65% of total EV sales in the sample cities during our data period. The size of the EV stock by

[30] BYD started as a rechargeable battery manufacturer in 1995 and entered the automobile business in 2003. It is the largest EV producer by volume in China and supplies batteries to all BYD models. CATL was founded in 2011 and specializes in the manufacturing of lithium-ion batteries for electric vehicles and energy storage systems. It grew quickly to become the largest battery supplier for EVs in China.

[31] Source: bloom.bg/2LiZSu5

institutions could affect the investment decisions on charging stations. A similar strategy is used in Corts (2010) to study the investment decision of flex-fuel charging stations. The identification assumption is that the lagged institutional EV stock is unlikely to be correlated with concurrent demand shocks to individual buyers. Our results hold when we use the second lag of the institutional EV stock.

To address potential policy endogeneity due to unobserved local demand shocks, we use a city-border regression design, similar in spirit to studies such as Holmes (1998); Dube et al. (2010); Hagedorn et al. (2015); Barwick et al. (2017). The design exploits the fact that local policies change sharply across city borders, but other demand factors such as transportation costs, access to dealer stores, and consumer preference are likely to be similar among neighboring cities.[32] In practice, we group adjacent cities into a cluster of multiple cities. Among the 150 cities, we create 34 clusters with each cluster having 4.4 cities. Each cluster includes at least one city that is among the top 40 EV cities (e.g., a major city). To control for time-varying local unobservables common in each cluster, we include cluster-time fixed effects, and cluster-brand-year fixed effects. Cluster-brand-year fixed effects control for demand shocks that are specific to each brand in a cluster for example due to the change in dealer presence or consumer preference for a brand among the cities in a cluster. In a robustness check, we restrict the clusters to include only bordering cities with average household income less than 20% different from the major city in the cluster. This leaves 31 clusters with 106 cities. The results are very similar to those with 150 cities.

4 Estimation Results

We first present estimation results for the main specifications and then results from robustness checks.

4.1 Parameter Estimates

Table 4 reports the estimation results of the demand model in Equation (1) from eight specifications. All the regressions include consumer price, the total number of charging ports, the dummy variable for exemption from driving restriction, the dummy variable for green plate policy, and three key vehicle attributes: vehicle size (length by width), power over weight, and

[32]Subsidies are tied to the city of residence.

driving range. The first five columns are from OLS while the last three are from IV. The last column is our preferred specification and the results are used in the policy analysis below.

From column (1) to (5), we successively add more controls to examine the effects of potential confounding factors on our key parameters of interest. Column (1) include city-model fixed effects to control for city-specific but time-invariant consumer preference or demand shocks for each model. All the coefficient estimates have intuitive signs and are statistically significant. Bearing in mind that these estimates may not be consistent, the results suggest that: (1) a subsidy of ¥10,000 increases EV sales by 7.2% ; (2) an increase of 1,000 charging ports increases EV sales by 3.6%; (3) the exempt from driving restriction increases EV sales by over 50%; and (4) the green plate policy increases EV sales by nearly 30%.[33] Column (2) adds time (year-quarter) fixed effects to control for national time-varying demand shocks. Including time fixed effects meaningfully changes the coefficient estimates for the number of charging ports, green plate policy, and driving range, suggesting the time-varying unobservables as important confounders for these three variables of interest.

Column (3) adds city-year fixed effects to control for city-specific demand shocks that vary from year to year. There are two significant changes on the coefficient estimates. First, the estimate on the number of charging ports become statistically significant and the magnitude stays roughly the same in all the remaining specifications. The key variation for identifying the effect of charging infrastructure in column (3) is within-city quarter-to-quarter variation in the number of charging stations within a year. Second, the coefficient estimate on the driving restriction exempt policy decreases and becomes statistically insignificant for the remaining specifications. By removing the year-to-year variation in the policy, the identification relies solely on the within-city within-year changes in the policy status. That is, the identification is based on the limited cases where the policy was adopted mid-year in the city. There is limited quarter-to-quarter variation within a year in policy adoption as suggested by Appendix Figure A1. The result suggests that the policy does not significantly incentivize consumers to switch from gasoline vehicles to EVs. This could be due to the weak enforcement of the policy or consumers' adaptive behavior in their travel decisions. Driving restriction only applies to peak hours within city center and consumers could change their travel time or even travel mode (e.g., using public transit) without having to resort to buying EVs.

As discussed in Section 3.1, one of the key identification challenges is the time-varying and

[33] The percentage impact of a policy dummy on EV sales can be consistently estimated by 100*$[exp(\hat{\beta} - \widehat{var}(\hat{\beta})/2) - 1]$.

city-specific demand shocks. In order to examine the effect of charging infrastructure on EV demand, it is not practical to include city-time fixed effects. Instead, we use a border regression design in columns (4) to (8) where bordering cities are classified into clusters. Column (4) adds cluster-time fixed effects and relies on cross-city within-cluster variation as the key source of variation in identifying the effect of charging infrastructure and policy variables. Intuitively, if a city has a larger increase in the number of charging ports relative to the change in other cities within the same cluster during a given quarter, and it also observes a larger increase in EV sales during the same period, these commensurate changes would suggest a positive impact of access to charging infrastructure on EV demand. The identification assumption is that the larger increase in the number of charging ports in the city is exogenous to concurrent city-specific demand shocks for EVs. Similarly, the effect of the green plate policy is identified from contemporaneous policy variation within the same cluster. The coefficient estimate on the charging port increases slightly but the effect size of the green plate policy increases by two-thirds. Column (5) further adds cluster-brand-year fixed effects to control for brand-specific brand shocks that are common in each cluster but vary by year, such as the change in dealer presence of a brand or advertising efforts of a brand in a region. These fixed effects also control for year-to-year changes in consumer preference or product quality by brand. The coefficient estimate on vehicle size becomes negative and imprecise while that on driving range becomes positive and precisely estimated.

With the border regression design and the rich set of the fixed effects, one might still worry about potential endogeneity in consumer price due to unobserved product attributes, and in the number of charging ports due to simultaneity and unobservables. We address this issue in columns (6) to (8) using IV. Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy, and battery capacity interacting with supplier dummies (CATL, BYD, and others). In column (8), we instrument both price and the number of charging ports by adding one more IV, the stock of institutional EVs as of the previous quarter.

The IVs in columns (6) to (8) produce strong first-stage and they pass the weak identification test in all three specifications. The key difference between column (5) and columns (6) to (8) is the price coefficient estimate more than doubled in magnitude. This is consistent with the finding in the literature that unobserved product attributes tend to bias consumer price sensitivity to zero. The comparison highlights that OLS results would dramatically under-estimate the impact of subsidies on EV diffusion. Nevertheless, the estimation results across columns (6) to (8) are very close in magnitude. This suggest that the number of charging ports could be reasonably taken as exogenous to current demand shocks after controlling for time fixed effects, and city-year fixed effects, likely due to its nature of being a stock variable.

Taking the estimates from the last column as the preferred results, the estimates suggest that (1) a subsidy of ¥10,000 increases EV sales by nearly 16% ; (2) an increase of 1,000 charging ports increases EV sales by 20%; (3) the exempt from driving restriction does not seem to impact EV sales; and (4) the green plate policy increases EV sales by nearly 37%. The coefficient estimate on the price variable implies the own-price elasticity of -2.5 for a vehicle at the average price of ¥158k. The implied price elasticity is in line with the estimates from recent studies on EVs in other countries. For the US EV market, Li et al. (2017) estimates a price elasticity of -1.3 based on the initial stage of EV sales from 2011-2013 using a similar empirical framework. Xing et al. (2019) provides an elasticity estimate of -2.7 using a rich random coefficient discrete choice model with the second-choice data from US consumer surveys. Based on California data, Muehlegger and Rapson (2019) reports a price elasticity estimate from -3.1 to -3.9 among households with an annual income less than $100k. Springel (2019) estimates the price elasticities for EVs to be between -1 to -1.5 in the Norwegian EV market. In the policy analysis section below, we further discuss the implications of our parameter estimates and compare our findings with those in the literature.

4.2 Alternative Specifications

We estimate several alternative model specifications to examine the robustness of our findings. First, we replace consumer price in Equation (1) with its logarithm, leading to a log-linear specification. The semi-log specification estimated above implies the price elasticity being larger in magnitude for more expensive vehicles while the log-linear specification implies a constant price elasticity across products. The results are presented in Table 5 with the eight columns corresponding to those in Table 4. The coefficient estimate on log(consumer price) gives the price elasticity and it is -2.36 in column (8), very close to the average price elasticity of -2.5 from the semi-log specification. The parameter estimates on the number of charging ports and policy variables are very similar to those in Table 4.

In both Tables 4 and 5, the dependent variable is log(sales) as specified in Equation (1). There are 13% of observations with zero sales. The observations concentrate among less popular models and in small cities. We added 0.5 to the sales for these observations in order to keep them in the sample instead of dropping them as these observations could contain useful information for consumer demand. For example, if zero sales are more likely to occur in cities with less generous policy incentives, it would help us identify the effects of the policies. To examine the robustness of our results to the ad hoc method of using 0.5 to replace 0, we replace the dependent variable in Equation (1) with the inverse hyperbolic sine function which has a value of zero at zero but a similar shape with the logarithm function at a positive support. Tables 6 and 7 present coefficient estimates corresponding to those in Tables 4 and 5. The coefficient estimates are similar in magnitude and the qualitatively findings remain the same across these two sets of tables.

The demand equation (1) takes a convenient form for the purpose of estimation and interpretation rather than being derived from an underlying utility maximization framework. However, with a slight modification of the dependent variable, equation (1) could be consistent with a stylized utility maximization framework. In particular, the dependent variable would be $ln(s_{kit}) - ln(s_{0mt})$ where s_{kmt} is the market share of trim/choice k in market c and time t and s_{0mt} is the share of consumers who do not purchasing an EV (i.e., choose an outside option instead). This (linear) logit demand function is an aggregation of choices made by individuals with homogeneous consumer preference (Berry, 1994). Appendix Table A1 and A2 provides the estimates of the logit model. The implied price elasticity can be derived based on the price coefficient estimate in Appendix Table A1 as $\hat{\beta}_1 * p_k * (1 - s_k)$ or based on the estimate in Appendix Table A2 as $\hat{\beta}_1 * (1 - s_k)$. The implied price elasticities are very similar between the two sets of tables since s_j is close to zero. In addition, the coefficient estimates on other variables are nearly identical as well.

It is important to note, with only EV models in our data, our analysis treats all other non-EV models to be in one category (i.e., the outside good). Limiting the choice set and the substitution pattern across choices could potentially impact the estimate of the price elasticity and policy simulations below. EV models represent a technology that is dramatically different from conventional gasoline vehicles, therefore consumers are likely to consider them as a separate category in making purchase decisions. Different from the US market, traditional hybrid vehicles are nearly nonexistent in the Chinese market, limiting the possibility of substitution between PHEV and the traditional hybrid vehicles. EVs only represent about 4.4% of new vehicle sales in 2018. Including gasoline models in our regressions does not meaningfully change the estimates on the key variables of interests. Nevertheless, identifying the nuanced substitution pattern is important in understanding the environmental benefit of the policies as shown in Xing et al. (2019). As demonstrated in that study using US data, the micro-level data with the second-choice information is much better suited to assess the substitution pattern between EVs and non-EVs than the aggregate data using in this study. We leave it for future research.

As discussed above, the border regression design relies on the identification assumption that unobserved confounding factors are common across cities within a cluster due to the fact that cities in the same cluster tend to be similar. Nevertheless, some neighboring cities could have large difference in household income, likely the most important demographic variable in affecting EV demand. If large differences in household income translate to large differences in unobserved demand shocks across cities, including these cities could invalidate our key identification assumption. In alternative specifications, we remove the neighboring cities whose average household income is more than 20% different from the major city in the cluster (the city with the largest EV sales). This subsample includes 106 out of the 150 cities. The regression results based on the subsample are presented in Appendix Tables A3 and A4, corresponding to Tables 4 and 5. The results based on the subsample are very similar to those from the full sample, providing support for the key identification assumption behind the border regression design.

Heterogeneity analysis Appendix Table A5 presents regressions with interaction terms to examine heterogeneity. We first interact total subsidy with number of charging ports to examine whether there is complementarity between financial subsidies and investment of charging ports. The estimate coefficient for all OLS specifications are positive and significant. The IV estimates are still positive while not precise. The result is in line with the intuition that when more charging ports are available, subsidies could have a larger impact on stimulating EV adoption. We then interact driving restriction exemption with the green plate policy to examine the presence of policy interaction. The coefficient estimate from the preferred specification in column (8) is positive but not statistically significant. The coefficient estimate on the gasoline price has an counter-intuitive sign but is not statistically significant. Similarly, one might be interested in the impact of electricity prices on EV demand: higher electricity prices could deter EV purchase. However, electricity price (on average ¥0.5 per kwh) is low enough to be a significant cost factor in vehicle purchase decisions. In practice, there is very limited within-year variation in average electricity prices. The interaction between vehicle size and income is to capture consumer preference heterogeneity based on income. Intuitively, high-income households may have a stronger demand for larger vehicles for safety and comfort. The coefficient for the interaction term is positive and statistically significant in column (2)-(4), and positive but not precise in our preferred specification in column (8). The last interaction is between driving range and the number of charging ports. The availability of charging ports should alleviate driving range and hence benefit vehicle models with a lower range disproportionally more. Again, the coefficient estimate on the interaction term is neither intuitively signed nor precise.

Nonlinear analysis Appendix Table A6 shows the results with quadratic term of number of charging ports to check whether there is nonlinear effect. The intuition is that as more charging ports have been available, the impact from an additional unit of charging port could be decreasing. The estimates of the square term agree with this pattern. In all columns except for column (3), the sign of the coefficient is negative, but none of them are significant. There might be a threshold effect whereby the size of the charging infrastructure needs to reach a critical point to sustain EV demand in the long run. Zhou and Li (2018) study the critical mass issue in the EV market in the US and found that in many cities in the US, the EV market exhibits multiple equilibria. This implies that the number of charging stations need to pass a critical threshold and otherwise, the EV adoption will converge to zero in the long run. We leave this question for future research.

5 Policy Analysis

In this section, we conduct simulations to examine the role of the underlying driving factors behind the dramatic growth of China's EV market. Based on the model estimates, we simulate the counterfactual EV sales by removing each policy or non-policy factor one at a time.

5.1 Consumer Subsidies

The average subsidy from the central government is ¥34,600 with a range of ¥0 to ¥55,000 during our sample period. The average local subsidy is ¥9,800 with a range of ¥0 to ¥60,000. Together, the total subsidy amounts to ¥44,400 (or about $7,000) per EV, or nearly 26% of MSRP on average and as high as 73%. The total subsidies from the central and local government are nearly ¥55 billion during our sample period for the 150 cities.[34]

To examine the impact of consumer subsidies on EV sales, we simulate the EV sales without the subsidies based on the results of column (8) in Table 4. The simulated sales and the 95% confidence interval are depicted in Figure 9. The results suggest that the subsidies played an important role in promoting EV sales: they explained nearly 55% of the EV sales during the data

[34]The total consumer subsidies from both central and local government from 2011 to 2019 account to nearly ¥300 (or nearly $50 billion) including subsidies to commercial vehicles. Source: http://www.21cnev.com/html/201912/783429_1.html.

period. Appendix Figure A2 present simulation results based on the results using the subsample of 106 cities as shown in Table A3. The effect size is similar to the baseline estimate. The significance of consumer subsidies in the diffusion of alternative fuel vehicles (hybrid vehicles and EVs) has been documented in previous studies in other countries. Li et al. (2017) estimates the federal tax credit of $2,500 to $7,500 per EV contributed to about 40% of EV sales during 2011 to 2013 in the US. Springel (2019) finds that the subsidies on consumer purchases and charging stations explained about 37% of EV sales during 2011 to 2015 in Norway.[35] Comparing these estimates, the effect of consumer subsidies is stronger in China due to the larger price sensitivity among Chinese consumers as discussed above.

5.2 Green Plate Policy

Under the green plate policy, EVs are given special license plates in green color, distinctive from the license plates for gasoline vehicles. The policy rolled out in three waves: the first wave was in December 2016 with 5 cities; the second wave was in November 2017 covering 12 additional cities; and the third wave was in 2018 covering the rest of the country.

Our regressions suggest a robust and large effect of this policy on EV sales. The preferred specification in Table 4 suggests that the green plate policy is equivalent to about ¥20,000 subsidies in promoting EV sales. Based on the parameter estimates, Panel (b) in Figure 9 depicts the counterfactual sales by removing the green plate policy and shows that the policy contributed to nearly 18% of EV sales during our sample period. A similar effect is shown in Panel (b) in Appendix Figure A2 using the subsample of 106 cities. The efficacy of the policy is substantial and may appear to be too large to be true considering that the cost of the policy is likely to be minimal. However, the coefficient estimate on the green plate policy variable across all specifications are economically large and statistically significant. This finding highlights the large value that the green plate brings to consumers potentially through multiple channels.

Recent literature has find that consumers demonstrate their environmental preferences through buying green products (Kahn, 2007; Kahn and Vaughn, 2009) or choose to buy green products in order to seek status. Sexton and Sexton (2014) define conspicuous conservation as a phenomenon where individuals seek status conferred upon demonstration of austerity that minimizes the environmental impact of consumption. In the context of vehicle purchases, they

[35] Norway has the highest EV penetration in the world, nearly 56% of new vehicle sales by 2019 increasing from 25% in 2015. EVs are exempt from the valued-added tax of 25% levied on all new vehicle purchases. The tax exempt is equivalent to $8,250 for an EV with an average price of $33,000 during 2011-2015.

find that consumers are willing to pay an additional \$430–\$4,200 for the distinctively designed Toyota Prius. Our finding is also consistent with the findings from the eco-labeling literature that eco-labeling can help guide consumer purchasing decisions and encourage behavioral change of consumers and producers towards sustainability (Teisl et al., 2002; Bjørner et al., 2004; Mason, 2013).

5.3 Charging Infrastructure

As in many new technology markets, the EV market is characterized by indirect network effects in that the demand for EVs depends on the availability of publicly-accessible charging stations and the supply of charging infrastructure depends on the installed base of EVs. An inherent challenge in the development of this type of market is the coordination problem whereby one group of market participants tends to wait for the other group to act before taking their own action.[36] Policies such as subsidies that strengthen one side of the market could help the development of the other side. From the perspective of the government expenditure, the government could subsidize EV purchases or the investment of charging stations. Whether the policies on either side of the market are equally effective or not in promoting EV sales (i.e., the symmetry/neutrality of the policies) is an empirical question that has important implications on effective policy design.

The preferred specification in Table 4 shows that an increase of 1,000 charging ports is equivalent to ¥12,700 consumer subsidies in promoting EV sales. To examine the issue of neutrality, we examine the average cost of per induced EV sales from charging station investment, and from consumer subsidies separately during our data period. The total consumer subsidies during our data period amount to ¥55 billion, and the total sales induced by these subsidies were 561,495 (or 55% of all EVs sold). These numbers imply an average government cost of ¥98,000 to induce consumers to buy one extra EV through consumer subsidies.

To calculate the total investment cost of charging ports, we assume that average cost of an AC charging port is ¥10,000 while that of a DC charging port is ¥100,000 during our data period.[37] There are 132,207 AC charging ports and 65,902 DC charging ports constructed during our data period. The total cost would have been ¥7.92 billion. Since our data only capture

[36] More broadly, the consumer's benefit from adopting the primary good (i.e., EVs) depends on the availability of complementary goods (i.e., charging stations) while an investor's benefit from supplying the complementary goods depends on the installed base of the primary good. The interdependence is referred to as an indirect network effect. Examples of this type of market include computer hardware and software, CD players and CDs, video game consoles and games, and eReaders and eBooks.

[37] Source: https://zhuanlan.zhihu.com/p/20800474. The cost has reduced by about 20-30% by 2020. https://www.shangyexinzhi.com/article/547872.html.

60% of all public charging stations, this implies the total cost of ¥13.2 billion for all public charging stations in the sample cities. The total induced sales by the availability of the charging infrastructure are estimated to be 501,313 during our data period based on results in Table 4. These results imply an average government cost of ¥26,350 to induce consumers to buy one extra EV through subsidizing/investing charging stations. This cost estimate is an under-estimation of the effectiveness of the charging infrastructure since these charging stations will continue to contribute to future sales of EVs that we do not include in our calculation.

The estimates above suggest that investing in charging station is nearly four times as effective as subsidizing consumer purchases in promoting EV sales from the perspective of government expenditure. The better cost-effectiveness of charging infrastructure in promoting EVs is consistent with the finding in other countries. Both Li et al. (2017) and Springel (2019) show that subsidizing charging stations is more than twice as effective as subsidizing consumer purchases on a per dollar basis in the US and Norway, respectively. Both studies also find that the effect of subsidies on charging stations tapers off as the charging network gets larger. The former uses aggregate sales data by city from 2011 to 2013 while the latter uses individual registration record from 2011 to 2015. Our finding of the relative cost-effectiveness is even more striking given that our data is from 2015 to 2018 and the fact that Chinese consumers appear to be more price sensitive than those two countries. The stronger cost-effectiveness of subsidizing charging station in China than in US and Norway could be driven by the following features of housing and urban structure in China: the vast majority of city residents in China live in apartment complexes and do not have space to build private charging; and cities are denser, which allows public charging stations to serve more drivers.

6 Conclusion

This study provides to our knowledge the first empirical analysis on the underlying driving factors behind the rapid growth of the world's largest EV market, China. The analysis is based on the most comprehensive data on China's EV market including EV sales, charging infrastructure, and various central and local policies during 2015-2018. There are three key findings. First, generous consumer subsidies from both central and local government played a crucial role and explained at least half of the EV sales during our data period. Second, while the green plate policy has a low program cost, its impact is substantial and highlights the important psychological and social dimensions of the diffusion of environmentally friendly technologies. Third, the availability of charging infrastructure has a large effect on EV diffusion. Due to the strength of indirect network effects from charging infrastructure on EV demand, subsidizing charging station deployment is much more cost-effective than subsidizing EV purchases at the current diffusion stage.

These findings could offer important guidance on designing future EV policies in China and other countries. While it is the most commonly used strategy for the government to provide generous consumer subsidies to support the EV market, the strategy does not appear to be the most cost-effective one. Non-financial policies such as information provision on the potential environmental benefits of EVs and allowing consumers to signal their purchases through license plates or exterior designs could be low-hanging fruits in promoting the wider adoption of EVs. The early stage of the EV market can be reasonably characterized by "if you build it, they will come". Building charging infrastructure by the government is a cost-effective strategy to garner the indirect network effect in the market.

We conclude with four important directions for future research. First, understanding the pass-through of consumer subsidies could further shed light on the cost-effectiveness of this policy. Given the relatively low price sensitivity of EV buyers as well as other policies such as vehicle purchase restrictions that favor EVs in several major cities, it is not clear *a priori* how much consumers would have captured the subsidies. Second, although our empirical framework allows us to examine the aggregate impacts of policies and charging infrastructure on EV adoption, it does not capture the substitution pattern especially between EVs and gasoline models, a crucial element in evaluating the environmental impacts and welfare consequences of the new technology. Future research should rely on richer demand models and consumer-level data to better capture consumer choices among different EV and gasoline models, in order to evaluate the environmental impacts of EV adoption (Holland et al., 2016; Xing et al., 2019). Further, the cost-effectiveness of EV policies in terms of CO_2 reduction could be estimated based on the substitution pattern with additional information on the fuel source of electricity by location and ideally the generation profile depending on charging time. Third, our analysis focuses on the role of various factors in affecting consumer EV adoption. These factors could have had important impacts on the supply side through the product choices of automakers and R&D decisions of automakers and parts suppliers. A better understanding of the supply-side responses should further aid effective policy designs. Finally, while this study focuses on China, our research framework could be extended to country-level EV markets to explicitly include trade practices, in particular used vehicles trade, and other industrial practices. Lessons could be gleaned from the more comprehensive study to provide insight of how used vehicle trade impacts EV adoption and to offer important guidance on designing future EV policies in a global perspective.

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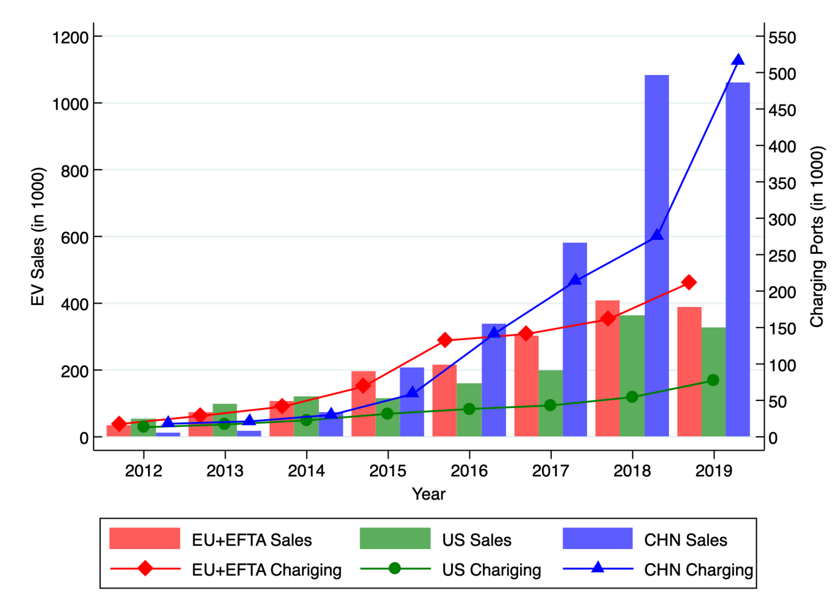
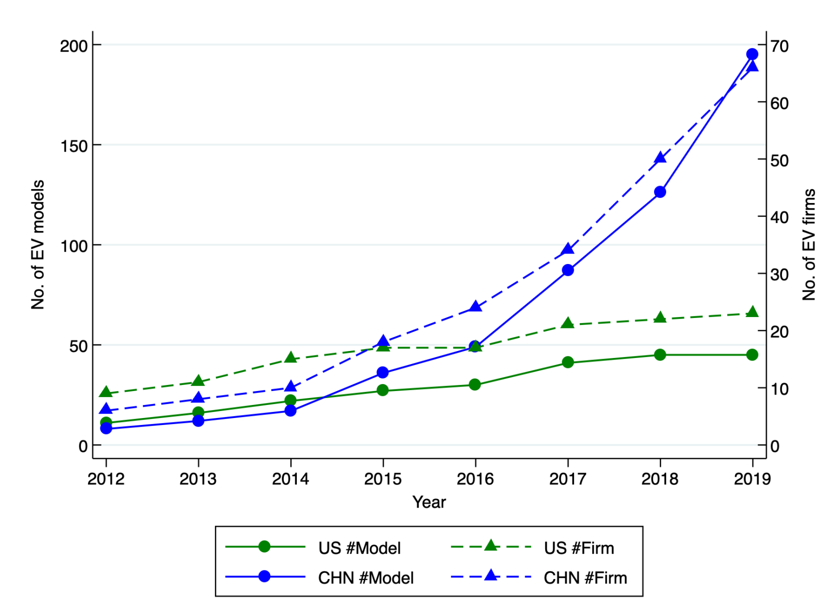
Figure 1: EV Sales and Charging Station by Country and Region



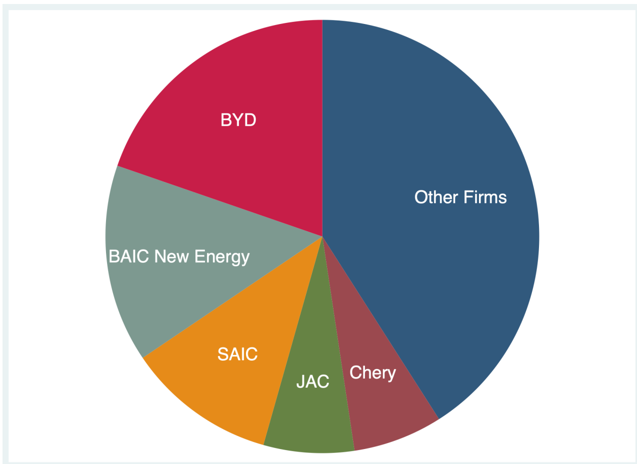
Notes: The figure plot passenger EV sales (bars) and charging outlets/ports (lines) separately for China, US, and EU and EFTA (Iceland, Liechtenstein, Norway, and Switzerland) combined. EVs include both battery EVs (BEVs) and plug-in hybrid EVs (PHEVs). Source: International Energy Agency, and marklines.com

Figure 2: Number of EV Firms and Models



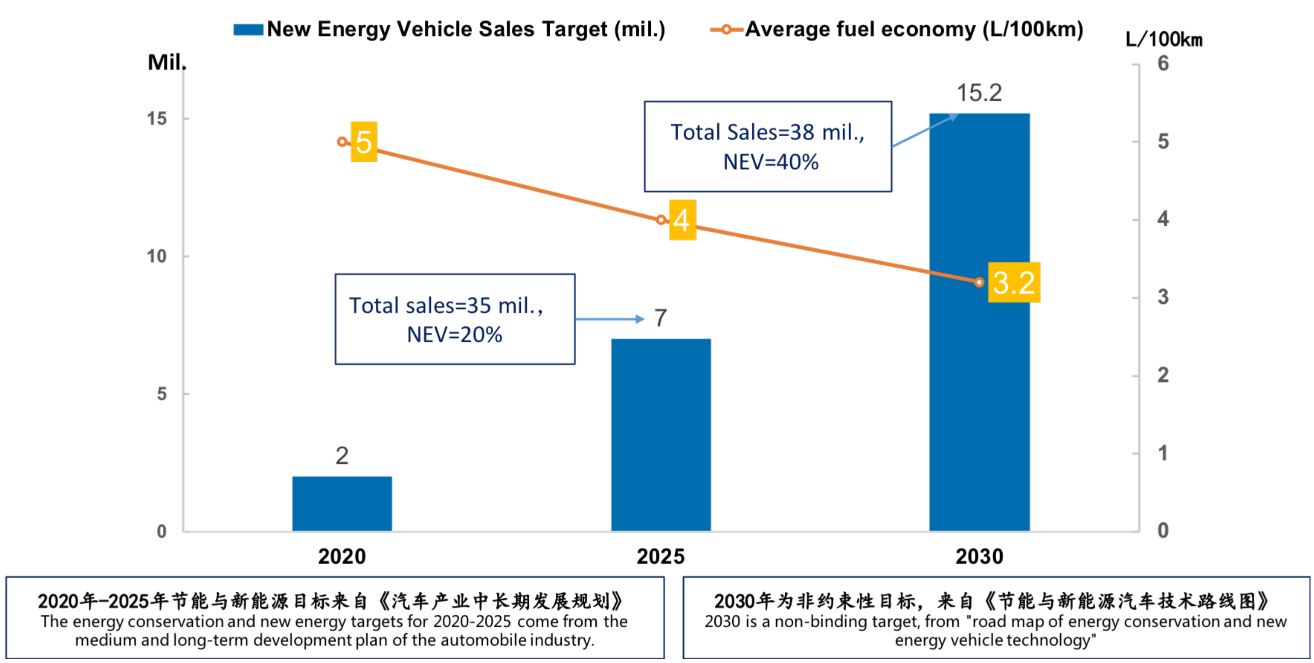
Notes: This figure shows the No. of EV firms and models (BEVs and PHEVs) in China and US. Data for China is up to May 2019.

Figure 3: Top 5 EV Firms in China and US



Notes: This figure shows the top five automakers by EV sales and their market shares in China and US in 2018.

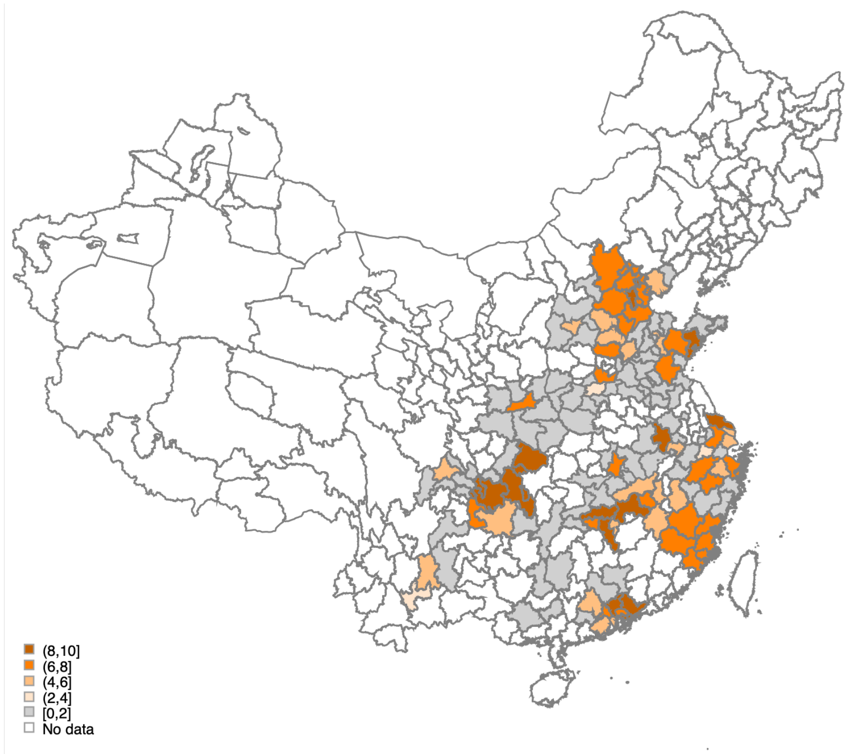
Figure 4: China's EV and Fuel Economy Targets



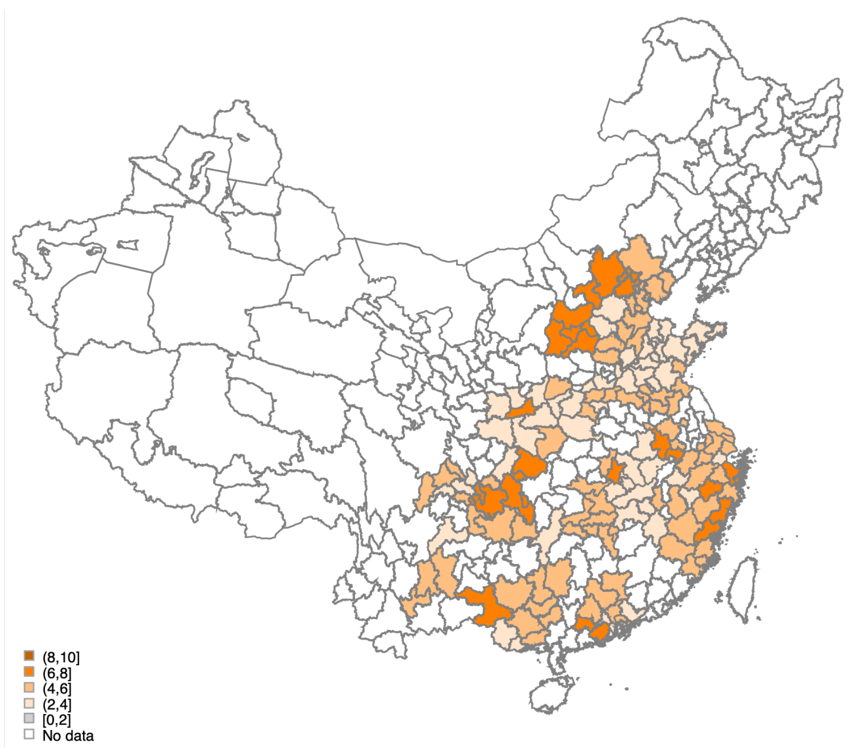
Notes: China's long-term national goals on EV sales, and average fleet fuel economy standards.

Figure 5: Consumer Subsidies across Cities

(a) 2015



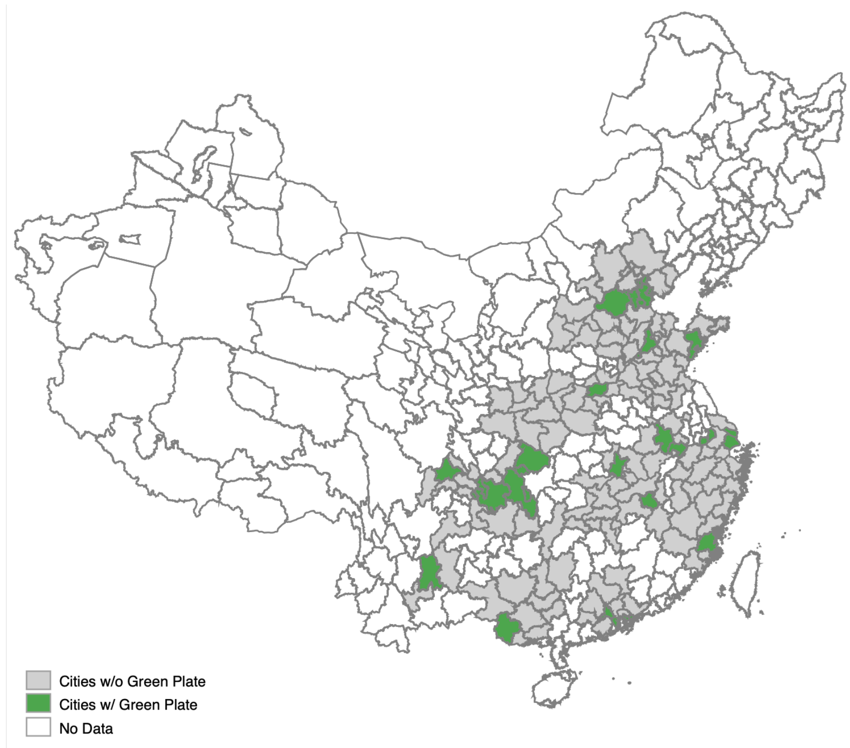
(b) 2018



Notes: Average consumer subsidies from central and local governments in ¥10,000 per EV in 2015 and 2018.

Figure 6: EV Green Plate Policy Rollout

(a) 2017

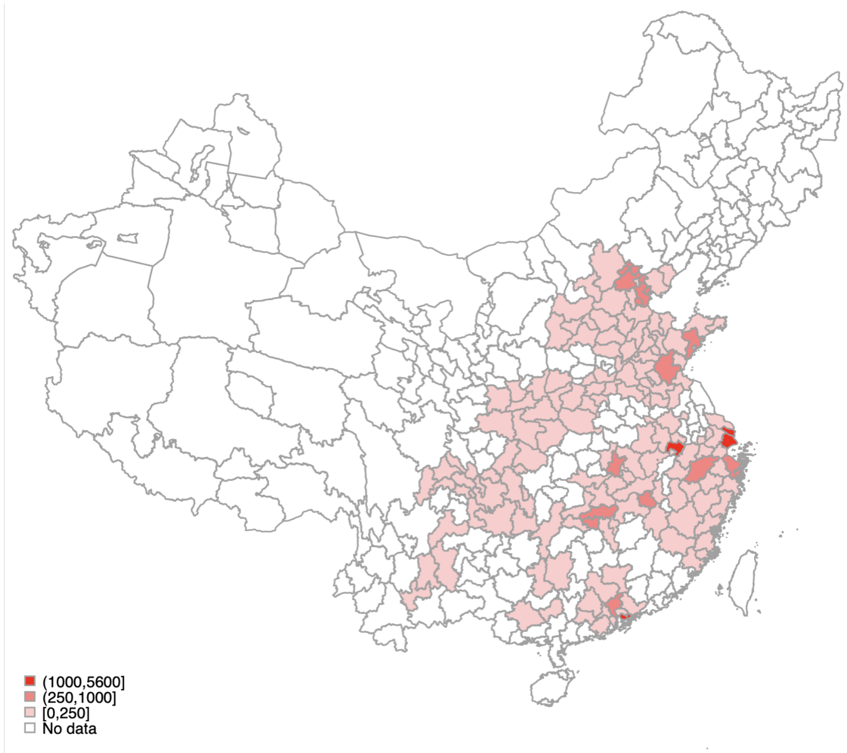


(b) 2018

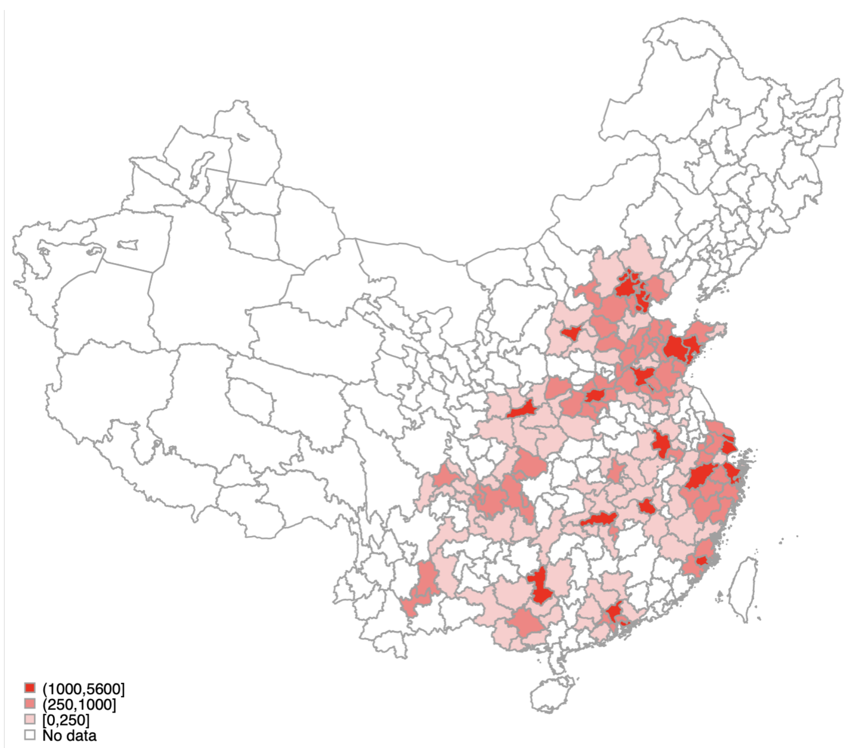
Notes: The rollout of green plate policy across cities. The policy started in 2016 with five cities: Shanghai, Nanjing, Wuxi, Jinan, and Shenzhen.

Figure 7: EV Sales per million Residents by City

(a) 2015



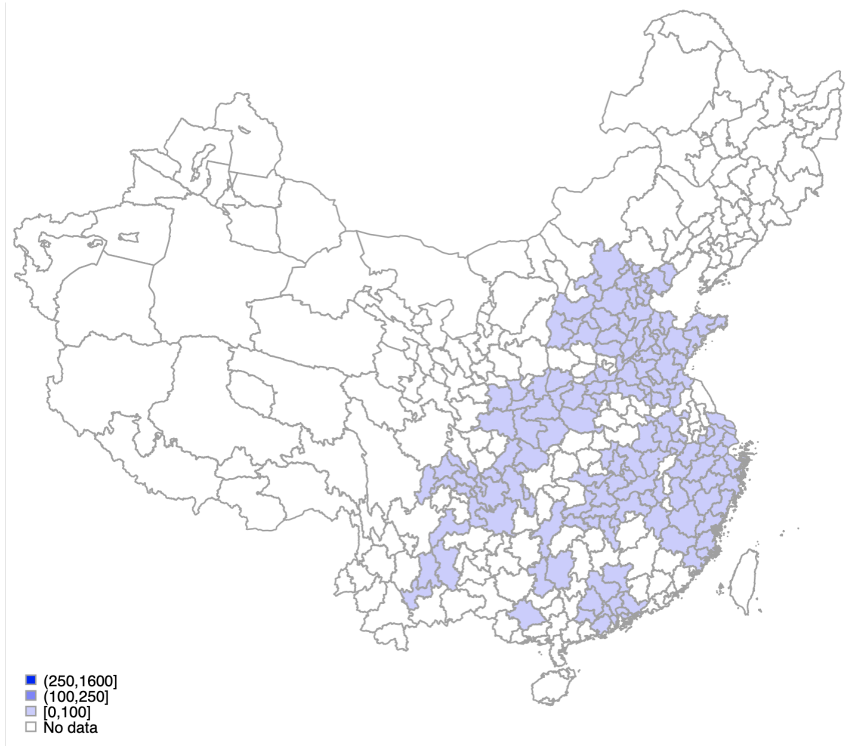
(b) 2018



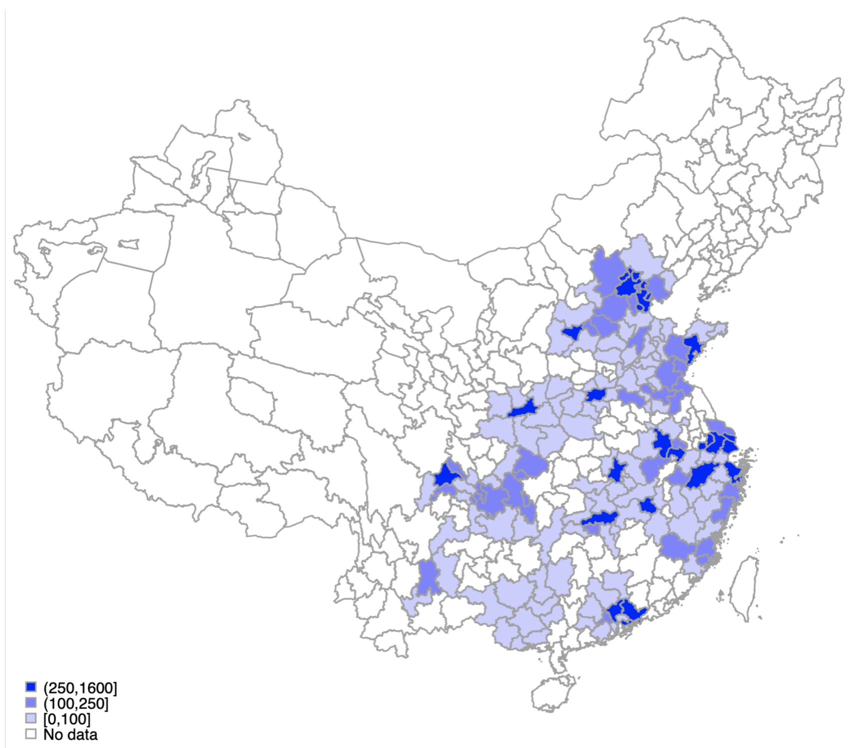
Notes: Annual EV sales (in units) per million residents by city for 150 sample cities in 2015 and 2018.

Figure 8: No. of Charging Ports per million Residents by City

(a) 2015



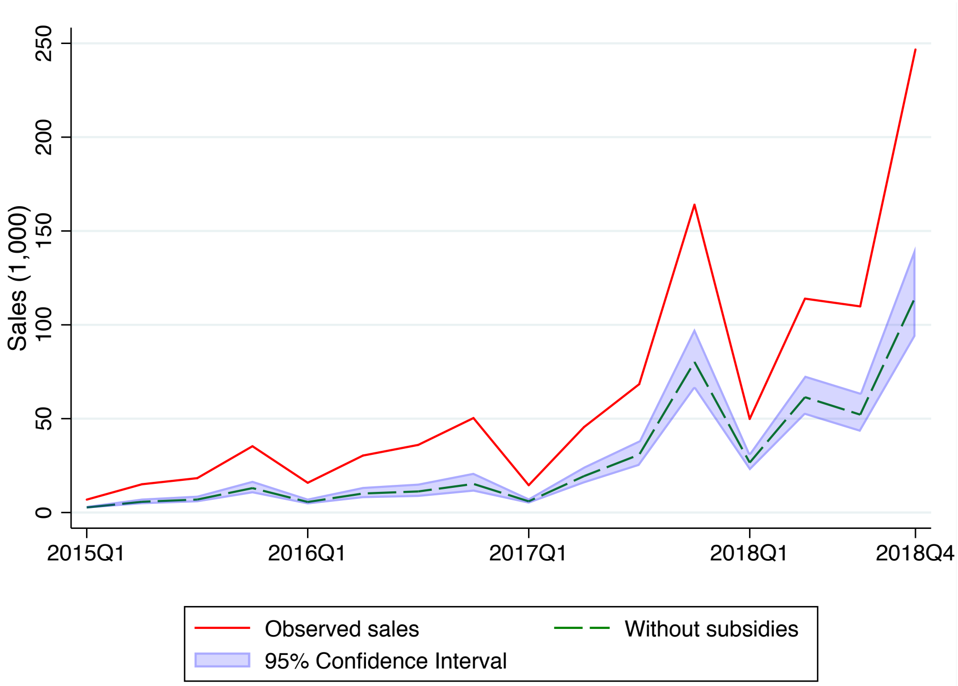
(b) 2018



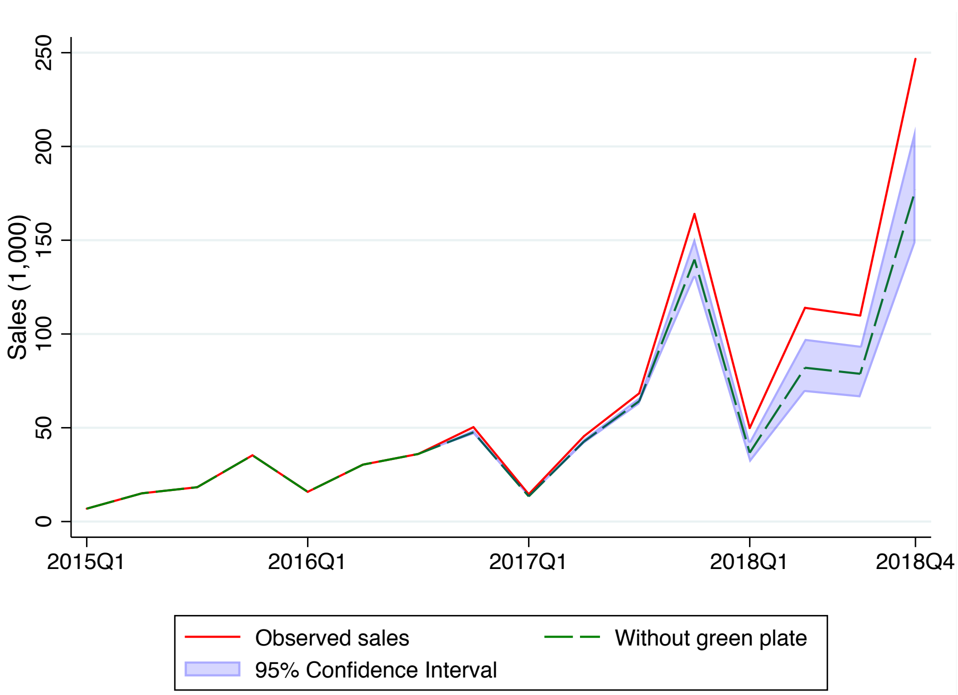
Notes: The number of charging ports per million residents by city for 150 sample cities by the end of 2015 and 2018.

Figure 9: Simulation Results

(a) Removing subsidies



(b) Removing green plate



Notes: The figures plot the counterfactual sales and the 95% confidence interval based on the estimation results from Table 4 with the full sample. Panel (a) removes central and local subsidies while Panel (b) removes the green plate policy. The sales would have been 45% and 82% of what have been observed in the data during the sample period, respectively.

Table 1: Consumer Subsidies in China and US

	Federal	Local
China	**Subsidy based on driving range** 2010: 10 pilot cities 2013: 88 pilot cities 2016: nationwide subsidy	Matched with central subsidy by 1:1 to 1:0.5 ratio Shared by provincial and city governments Total subsidy no more than 50% to 70% of MSRP
US	**Subsidy based on battery capacity** From 2010: $2500 for 4kWh battery, with an additional $417 per kWh to $7500 200k qualifying vehicles per automaker	Rebates: CA, IL, MA, NY, PA, TX Tax credit: CO, GA, LA, MD, SC, UT, WV Sales tax exemption or reduction: CO, NJ, WA Fee exemptions or reduced fee: AZ, IL

Table 2: Central Subsidies from 2013 to 2018

Type	Range	2013	2014	2015	2016	2017	2018
BEV	$\geq$ 80km	¥35,000	¥33,250	¥31,500	-	-	-
	$\geq$ 100km				¥25,000	¥20,000	-
	$\geq$ 150km	¥50,000	¥47,500	¥45,000	¥45,000	¥36,000	¥15,000
	$\geq$ 200km						¥24,000
	$\geq$ 250km	¥60,000	¥57,000	¥54,000	¥55,000	¥44,000	¥34,000
	$\geq$ 300km						¥45,000
	$\geq$ 400km						¥50,000
PHEV	$\geq$ 50km	¥35,000	¥33,250	¥31,500	¥30,000	¥24,000	¥22,000

Notes: This table shows the subsidies from the central government. The amount of subsidies is based on driving range. Starting from 2018, the subsidies are adjusted base on two additional requirements for EVs to be eligible: minimum energy efficiency (kWh/100km) as a function of vehicle weight, and battery energy density $\geq$ 105 Wh/kg. For comparison, the amount of EV subsidies in the US is only based on battery capacity.

Table 3: Summary Statistics

	Mean	S.D.	Min	Max
Sales	37.02	209.21	0.00	7834
MSRP (in ¥10,000)	20.01	8.25	8.18	60.88
Consumer price (in ¥10,000)	15.75	8.95	2.24	60.88
Total subsidy (in ¥10,000)	4.53	2.27	0.00	14.17
Central subsidy (in ¥10,000)	3.51	1.42	0.00	5.71
No. of charging ports (1,000)	1.62	3.99	0.00	36.65
No. of charging stations	177	446	0.00	3666
EV exempt from driving restriction	0.21	0.41	0.00	1.00
Green plate for EVs	0.54	0.50	0.00	1.00
Vehicle size (m^2)	7.21	1.58	3.75	9.85
Motor power (100kW)	0.87	0.71	0.09	4.80
Weight(ton)	1.23	0.45	0.51	2.19
Driving range (100km)	1.85	1.07	0.50	4.20
Battery capacity (kwh)	26.66	14.74	8.00	82.00
EV stock by institutions	5.86	12.68	0.00	81.44
Population (in mil.)	7.52	5.15	0.74	31.02
Income (in ¥10,000)	3.90	1.07	2.02	6.80

Notes: The unit of observation is city-quarter by vehicle trim. The number of observations is 27,577. The data is from 2015 to 2018 for 150 cities. MSRP is manufacturer suggested retail price.

Table 4: Regressions Results of EV Demand: Semi-log

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Consumer price (in ¥10,000)	-0.072***	-0.070***	-0.074***	-0.074***	-0.067***	-0.146***	-0.157***	-0.158***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.029)	(0.023)	(0.023)
No. of charging ports (1,000)	0.036*	0.006	0.171***	0.191***	0.193***	0.192***	0.192***	0.200***
	(0.020)	(0.015)	(0.032)	(0.034)	(0.034)	(0.034)	(0.034)	(0.039)
EV exempt from driving restriction	0.430***	0.459***	0.115	-0.012	0.034	0.030	0.029	-0.027
	(0.119)	(0.129)	(0.183)	(0.145)	(0.155)	(0.150)	(0.150)	(0.156)
Green plate for EVs	0.251***	0.133**	0.189***	0.308***	0.317***	0.314***	0.314***	0.316***
	(0.054)	(0.066)	(0.064)	(0.077)	(0.080)	(0.080)	(0.080)	(0.082)
Vehicle size (m^2)	0.526***	0.448**	0.370**	0.390**	-0.193	-0.114	-0.103	-0.162
	(0.186)	(0.177)	(0.184)	(0.189)	(0.182)	(0.182)	(0.176)	(0.181)
Power/weight (kW/kg)	8.629***	11.559***	12.615***	12.481***	10.129***	7.322***	6.932***	6.931***
	(2.029)	(2.072)	(2.122)	(2.123)	(2.078)	(2.362)	(2.166)	(2.167)
Driving range (100km)	0.132***	-0.036	-0.012	-0.005	0.149***	0.105**	0.099**	0.100**
	(0.036)	(0.037)	(0.037)	(0.038)	(0.047)	(0.048)	(0.047)	(0.047)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.494	0.553	0.563	0.565	0.563	-0.103	-0.105	-0.105
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						558.686	268.150	223.920
Underidentification stat						55.595	89.558	88.630
Weak Identification stat						558.686	268.150	223.920
Overidentification stat						0.000	21.860	21.518

Notes: The dependent variable is ln(sales). Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regressions Results of EV Demand: log-linear

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Ln(Consumer price)	-0.665***	-0.574***	-0.487***	-0.477***	-0.435***	-1.836***	-2.326***	-2.326***
	(0.108)	(0.105)	(0.124)	(0.128)	(0.151)	(0.362)	(0.348)	(0.343)
No. of charging ports (1,000)	0.035*	0.003	0.173***	0.192***	0.193***	0.195***	0.196***	0.203***
	(0.020)	(0.014)	(0.031)	(0.034)	(0.034)	(0.034)	(0.034)	(0.038)
EV exempt from driving restriction	0.419***	0.432***	0.113	-0.013	0.037	0.036	0.035	-0.019
	(0.116)	(0.124)	(0.182)	(0.147)	(0.156)	(0.149)	(0.147)	(0.153)
Green plate for EVs	0.274***	0.131**	0.193***	0.312***	0.318***	0.314***	0.313***	0.315***
	(0.053)	(0.066)	(0.063)	(0.076)	(0.080)	(0.080)	(0.080)	(0.082)
Vehicle size (m^2)	0.598***	0.495***	0.402**	0.421**	-0.203	-0.023	0.041	-0.013
	(0.184)	(0.178)	(0.186)	(0.190)	(0.182)	(0.182)	(0.175)	(0.180)
Power/Weight (kW/kg)	9.659***	12.327***	13.616***	13.488***	11.783***	9.403***	8.571***	8.619***
	(2.070)	(2.068)	(2.087)	(2.086)	(2.046)	(2.205)	(2.196)	(2.200)
Driving range (100km)	0.128***	-0.041	-0.005	0.002	0.159***	0.072	0.041	0.042
	(0.036)	(0.038)	(0.038)	(0.039)	(0.047)	(0.049)	(0.049)	(0.048)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.492	0.551	0.561	0.564	0.562	-0.116	-0.130	-0.130
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						401.988	173.500	144.575
Underidentification stat						53.847	83.076	82.335
Weak Identification stat						401.988	173.500	144.575
Overidentification stat						0.000	20.772	20.760

Notes: The dependent variable is ln(sales). Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regressions Results of EV Demand: asinh(sales) on price

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Consumer price (in ¥10,000)	-0.070***	-0.068***	-0.073***	-0.072***	-0.066***	-0.141***	-0.151***	-0.152***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.029)	(0.023)	(0.023)
No. of charging ports (1,000)	0.036*	0.007	0.169***	0.189***	0.190***	0.190***	0.190***	0.200***
	(0.020)	(0.015)	(0.031)	(0.033)	(0.034)	(0.034)	(0.034)	(0.038)
EV exempt from driving restriction	0.423***	0.457***	0.125	-0.005	0.041	0.037	0.037	-0.020
	(0.116)	(0.127)	(0.179)	(0.143)	(0.153)	(0.149)	(0.148)	(0.154)
Green plate for EVs	0.241***	0.129**	0.187***	0.303***	0.312***	0.310***	0.309***	0.312***
	(0.053)	(0.065)	(0.063)	(0.075)	(0.078)	(0.078)	(0.078)	(0.080)
Vehicle size (m^2)	0.515***	0.443**	0.368**	0.388**	-0.179	-0.105	-0.095	-0.151
	(0.183)	(0.175)	(0.182)	(0.186)	(0.179)	(0.179)	(0.173)	(0.178)
Power/Weight (kW/kg)	8.222***	11.180***	12.246***	12.115***	9.674***	7.012***	6.654***	6.659***
	(1.999)	(2.037)	(2.084)	(2.087)	(2.019)	(2.297)	(2.106)	(2.108)
Driving range (100km)	0.134***	-0.032	-0.009	-0.002	0.151***	0.109**	0.103**	0.104**
	(0.035)	(0.037)	(0.037)	(0.038)	(0.046)	(0.047)	(0.046)	(0.046)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.491	0.552	0.562	0.565	0.562	-0.102	-0.104	-0.104
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						558.686	268.150	223.920
Underidentification stat						55.595	89.558	88.630
Weak Identification stat						558.686	268.150	223.920
Overidentification stat						0.000	21.870	21.568

Notes: The dependent variable is the inverse hyperbolic sine of sales. Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

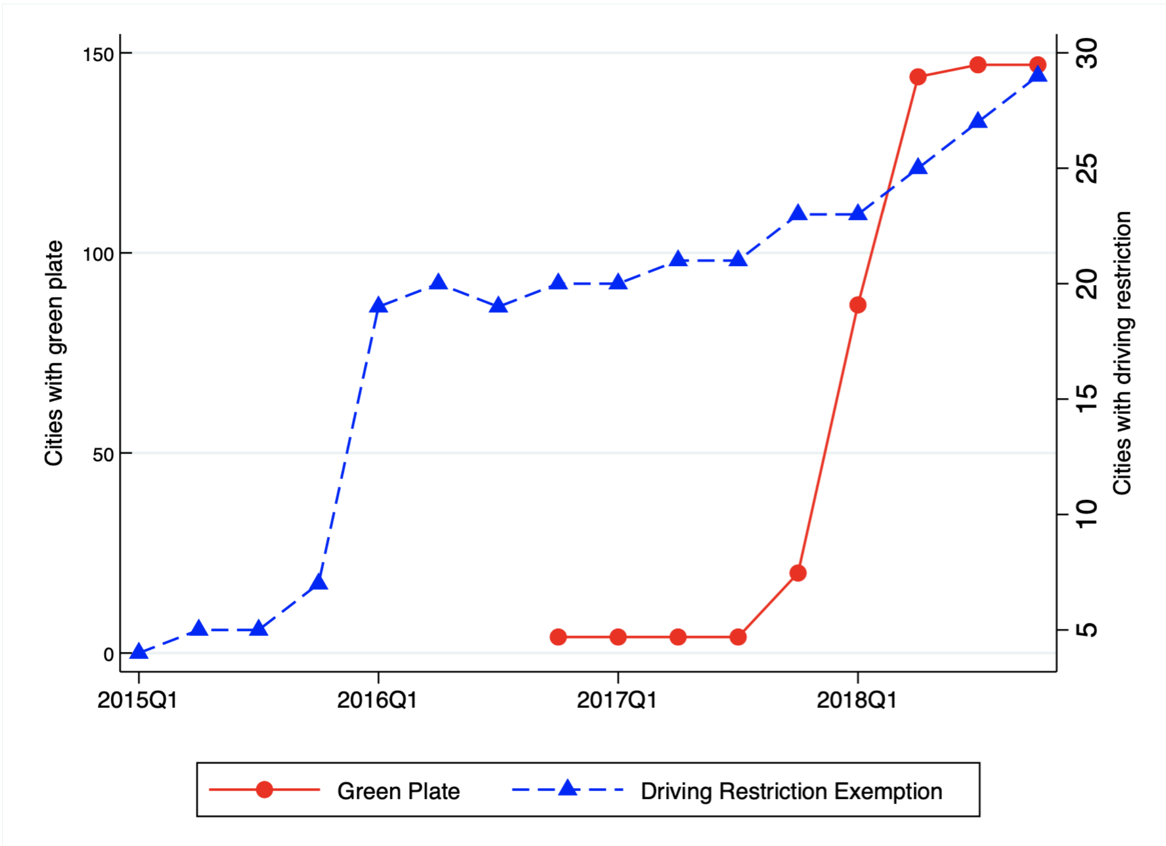
Table 7: Regressions Results of EV Demand: asinh(sales) on log(price)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Ln(Consumer price)	-0.648***	-0.561***	-0.480***	-0.470***	-0.432***	-1.772***	-2.246***	-2.246***
	(0.107)	(0.103)	(0.122)	(0.126)	(0.148)	(0.360)	(0.347)	(0.342)
No. of charging ports (1,000)	0.035*	0.004	0.171***	0.190***	0.191***	0.192***	0.193***	0.203***
	(0.019)	(0.014)	(0.031)	(0.033)	(0.034)	(0.034)	(0.033)	(0.037)
EV exempt from driving restriction	0.412***	0.431***	0.123	-0.006	0.044	0.043	0.042	-0.013
	(0.114)	(0.122)	(0.178)	(0.146)	(0.154)	(0.148)	(0.146)	(0.152)
Green plate for EVs	0.264***	0.127*	0.190***	0.307***	0.314***	0.310***	0.308***	0.311***
	(0.052)	(0.065)	(0.062)	(0.075)	(0.078)	(0.079)	(0.079)	(0.081)
Vehicle size (m^2)	0.585***	0.489***	0.399**	0.419**	-0.189	-0.016	0.045	-0.007
	(0.181)	(0.175)	(0.183)	(0.187)	(0.179)	(0.179)	(0.172)	(0.177)
Power/weight (kW/kg)	9.220***	11.929***	13.229***	13.104***	11.299***	9.021***	8.216***	8.269***
	(2.042)	(2.033)	(2.049)	(2.050)	(1.986)	(2.140)	(2.132)	(2.135)
Driving range (100km)	0.129***	-0.037	-0.002	0.005	0.160***	0.076	0.047	0.048
	(0.035)	(0.037)	(0.037)	(0.038)	(0.046)	(0.048)	(0.048)	(0.047)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.490	0.551	0.561	0.563	0.561	-0.115	-0.128	-0.128
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						401.988	173.500	144.575
Underidentification stat						53.847	83.076	82.335
Weak Identification stat						401.988	173.500	144.575
Overidentification stat						0.000	20.674	20.654

Notes: The dependent variable is the inverse hyperbolic sine of sales. Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Figures and Tables

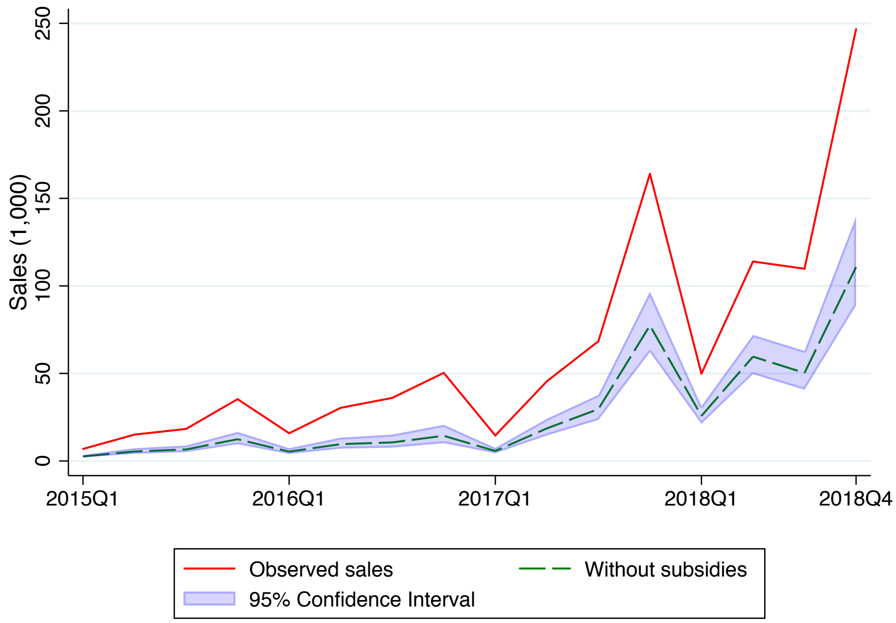
Figure A1: Policy Rollout over Time



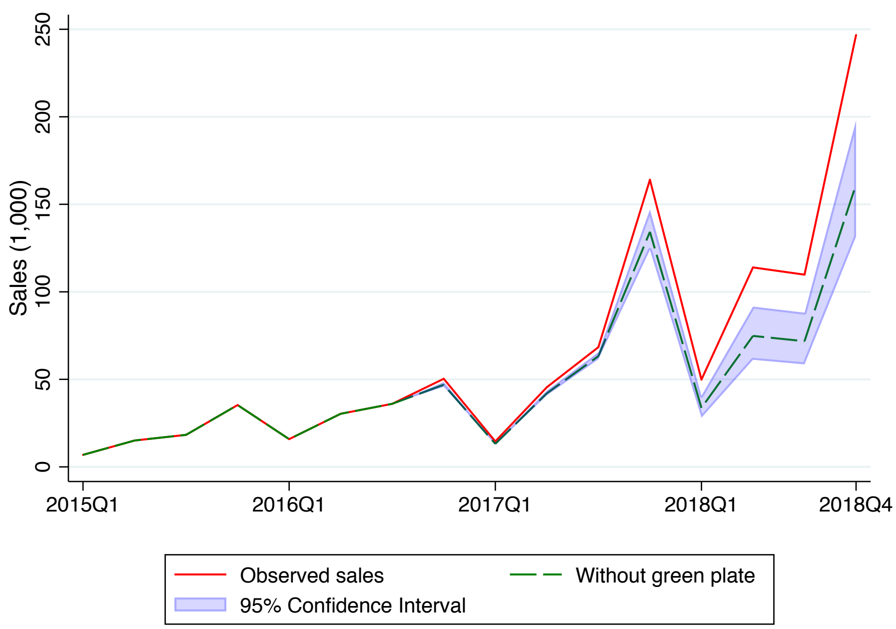
Notes: The figure plot the number of cities with driving restriction exemption and green plate by quarter from 2015 to 2018.

Figure A2: Simulation Results

(a) Removing subsidies



(b) Removing green plate



Notes: The figures plot the counterfactual sales and the 95% confidence interval based on estimation using 106 cities. Panel (a) removes central and local subsidies while Panel (b) removes the green plate policy. The sales would have been 43% and 78% of what have been observed in the data on average during the sample period, respectively.

Table A1: Regressions Results of EV Demand: Logit

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Consumer price (in ¥10,000)	-0.071***	-0.070***	-0.074***	-0.074***	-0.067***	-0.147***	-0.158***	-0.159***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.029)	(0.023)	(0.023)
No. of charging ports (1,000)	0.043**	0.012	0.184***	0.204***	0.206***	0.205***	0.205***	0.223***
	(0.018)	(0.012)	(0.031)	(0.036)	(0.037)	(0.037)	(0.037)	(0.040)
EV exempt from driving restriction	0.385***	0.458***	0.116	-0.017	0.028	0.025	0.024	-0.032
	(0.118)	(0.124)	(0.184)	(0.144)	(0.154)	(0.149)	(0.149)	(0.155)
Green plate for EVs	0.343***	0.145**	0.196***	0.324***	0.333***	0.330***	0.330***	0.333***
	(0.056)	(0.065)	(0.066)	(0.083)	(0.086)	(0.087)	(0.087)	(0.089)
Vehicle size (m^2)	0.570***	0.435**	0.368**	0.389**	-0.192	-0.114	-0.103	-0.161
	(0.186)	(0.176)	(0.185)	(0.189)	(0.182)	(0.182)	(0.176)	(0.181)
Power/weight (kW/kg)	8.627***	11.756***	12.562***	12.416***	10.053***	7.238***	6.848***	6.871***
	(2.031)	(2.065)	(2.123)	(2.123)	(2.079)	(2.362)	(2.166)	(2.168)
Driving range (100km)	0.165***	-0.040	-0.013	-0.006	0.149***	0.105**	0.099**	0.099**
	(0.036)	(0.038)	(0.037)	(0.038)	(0.047)	(0.048)	(0.047)	(0.047)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.472	0.537	0.547	0.551	0.547	-0.102	-0.104	-0.104
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						558.686	268.150	223.920
Underidentification stat						55.595	89.558	88.630
Weak Identification stat						558.686	268.150	223.920
Overidentification stat						0.000	21.774	21.441

Notes: This is the logit demand with the dependent variable being $ln(s_{kit}) - ln(s_{0mt})$ where s_{kmt} is the market share of trim/choice k in market c and time t and s_{0mt} is the share of consumers who are not purchasing an EV. Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Regressions Results of EV Demand: Logit

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Ln(Consumer price)	-0.657***	-0.569***	-0.488***	-0.478***	-0.436***	-1.840***	-2.329***	-2.329***
	(0.113)	(0.103)	(0.124)	(0.128)	(0.151)	(0.362)	(0.348)	(0.343)
No. of charging ports (1,000)	0.042**	0.009	0.186***	0.205***	0.207***	0.208***	0.209***	0.226***
	(0.018)	(0.011)	(0.031)	(0.036)	(0.037)	(0.037)	(0.036)	(0.040)
EV exempt from driving restriction	0.374***	0.431***	0.114	-0.018	0.031	0.030	0.030	-0.024
	(0.116)	(0.120)	(0.183)	(0.147)	(0.156)	(0.149)	(0.146)	(0.152)
Green plate for EVs	0.367***	0.142**	0.199***	0.328***	0.334***	0.330***	0.329***	0.332***
	(0.055)	(0.065)	(0.065)	(0.083)	(0.087)	(0.087)	(0.087)	(0.089)
Vehicle size (m^2)	0.641***	0.482***	0.400**	0.420**	-0.203	-0.022	0.041	-0.013
	(0.183)	(0.176)	(0.186)	(0.190)	(0.182)	(0.182)	(0.175)	(0.180)
Power/Weight (kW/kg)	9.644***	12.525***	13.564***	13.425***	11.709***	9.323***	8.491***	8.563***
	(2.079)	(2.063)	(2.089)	(2.085)	(2.047)	(2.206)	(2.197)	(2.201)
Driving range (100km)	0.161***	-0.044	-0.006	0.001	0.159***	0.071	0.040	0.041
	(0.036)	(0.038)	(0.038)	(0.039)	(0.047)	(0.049)	(0.049)	(0.048)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.470	0.535	0.545	0.549	0.546	-0.115	-0.128	-0.128
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						401.988	173.500	144.575
Underidentification stat						53.847	83.076	82.335
Weak Identification stat						401.988	173.500	144.575
Overidentification stat						0.000	20.696	20.695

Notes: This is the logit demand with the dependent variable being $ln(s_{kit}) - ln(s_{0mt})$ where s_{kmt} is the market share of trim/choice k in market c and time t and s_{0mt} is the share of consumers who are not purchasing an EV. Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Regressions Results based on Subsample: Semi-log

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Consumer price (in ¥10,000)	-0.072***	-0.070***	-0.074***	-0.082***	-0.074***	-0.152***	-0.167***	-0.167***
	(0.011)	(0.009)	(0.011)	(0.013)	(0.014)	(0.033)	(0.026)	(0.026)
No. of charging ports (1,000)	0.036*	0.006	0.171***	0.185***	0.180***	0.180***	0.180***	0.157***
	(0.020)	(0.015)	(0.032)	(0.039)	(0.040)	(0.040)	(0.040)	(0.038)
EV exempt from driving restriction	0.430***	0.459***	0.115	-0.038	0.008	0.011	0.012	-0.046
	(0.119)	(0.129)	(0.183)	(0.142)	(0.152)	(0.147)	(0.147)	(0.154)
Green plate for EVs	0.251***	0.133**	0.189***	0.403***	0.409***	0.406***	0.405***	0.407***
	(0.054)	(0.066)	(0.064)	(0.089)	(0.094)	(0.094)	(0.094)	(0.095)
Vehicle size (m^2)	0.526***	0.448**	0.370**	0.227	-0.310	-0.223	-0.206	-0.264
	(0.186)	(0.177)	(0.184)	(0.217)	(0.216)	(0.217)	(0.209)	(0.214)
Power/Weight (kW/kg)	8.629***	11.559***	12.615***	14.465***	10.913***	8.255***	7.747***	7.707***
	(2.029)	(2.072)	(2.122)	(2.279)	(2.267)	(2.539)	(2.342)	(2.333)
Driving range (100km)	0.132***	-0.036	-0.012	-0.003	0.161***	0.117**	0.109**	0.110**
	(0.036)	(0.037)	(0.037)	(0.042)	(0.052)	(0.052)	(0.052)	(0.051)
Observations	25003	25003	24995	20543	20400	20400	20400	20143
Adjusted R^2	0.494	0.553	0.563	0.565	0.561	-0.115	-0.118	-0.118
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						462.889	227.990	192.639
Underidentification stat						44.608	69.482	68.752
Weak Identification stat						462.889	227.990	192.639
Overidentification stat						0.000	23.726	23.367

Notes: The regressions are based on 106 cities in clusters that contain cities with similar average household income. The dependent variable is ln(sales). Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Regressions Results based on Subsample: log-linear

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Ln(Consumer price)	-0.665***	-0.574***	-0.487***	-0.558***	-0.527***	-1.927***	-2.502***	-2.491***
	(0.108)	(0.105)	(0.124)	(0.143)	(0.168)	(0.409)	(0.383)	(0.377)
No. of charging ports (1,000)	0.035*	0.003	0.173***	0.185***	0.181***	0.182***	0.182***	0.158***
	(0.020)	(0.014)	(0.031)	(0.038)	(0.040)	(0.040)	(0.040)	(0.039)
EV exempt from driving restriction	0.419***	0.432***	0.113	-0.042	0.008	0.020	0.025	-0.031
	(0.116)	(0.124)	(0.182)	(0.145)	(0.153)	(0.147)	(0.144)	(0.152)
Green plate for EVs	0.274***	0.131**	0.193***	0.409***	0.410***	0.407***	0.406***	0.408***
	(0.053)	(0.066)	(0.063)	(0.089)	(0.094)	(0.095)	(0.095)	(0.096)
Vehicle size (m^2)	0.598***	0.495***	0.402**	0.264	-0.319	-0.125	-0.046	-0.098
	(0.184)	(0.178)	(0.186)	(0.220)	(0.217)	(0.219)	(0.210)	(0.215)
Power/Weight (kW/kg)	9.659***	12.327***	13.616***	15.513***	12.586***	10.344***	9.424***	9.413***
	(2.070)	(2.068)	(2.087)	(2.236)	(2.236)	(2.388)	(2.396)	(2.393)
Driving range (100km)	0.128***	-0.041	-0.005	0.002	0.169***	0.081	0.044	0.046
	(0.036)	(0.038)	(0.038)	(0.043)	(0.052)	(0.054)	(0.054)	(0.053)
Observations	25003	25003	24995	20543	20400	20400	20400	20143
Adjusted R^2	0.492	0.551	0.561	0.564	0.559	-0.129	-0.145	-0.144
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						311.349	140.311	118.270
Underidentification stat						42.773	64.665	64.241
Weak Identification stat						311.349	140.311	118.270
Overidentification stat						0.000	22.165	21.868

Notes: The regressions are based on 106 cities in clusters that contain cities with similar average household income. The dependent variable is ln(sales). Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for both price and the number of charging ports using central subsidy, battery capacity, and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Heterogeneous Effects base on Full Sample: Semi-log

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Consumer price (¥10,000)	-0.064***	-0.060***	-0.062***	-0.061***	-0.060***	-0.132***	-0.149***	-0.133***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.012)	(0.032)	(0.025)	(0.025)
No. of charging ports (1,000)	0.024	-0.080**	0.106*	0.129**	0.140**	0.156***	0.160***	0.119**
	(0.020)	(0.032)	(0.060)	(0.050)	(0.058)	(0.057)	(0.056)	(0.053)
Subsidy*No. of charging ports (1,000)	0.022***	0.024***	0.014**	0.016***	0.013*	0.007	0.006	0.021
	(0.008)	(0.008)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.013)
EV exempt from driving restriction	0.568***	0.550***	0.134	-0.131	-0.081	-0.099	-0.103	-0.215
	(0.149)	(0.129)	(0.219)	(0.166)	(0.184)	(0.178)	(0.178)	(0.233)
Green plate for EVs	0.468***	0.161**	0.186***	0.264***	0.276***	0.272***	0.271***	0.250***
	(0.061)	(0.063)	(0.068)	(0.071)	(0.072)	(0.072)	(0.072)	(0.071)
Driving restriction*Green plate	-0.195	-0.161	-0.019	0.140	0.131	0.149	0.153	0.211
	(0.150)	(0.113)	(0.152)	(0.156)	(0.180)	(0.175)	(0.175)	(0.209)
Gasoline price (RMB/liter)	0.070	0.061	-0.048	-0.083	-0.125	-0.120	-0.118	-0.099
	(0.067)	(0.083)	(0.081)	(0.095)	(0.098)	(0.100)	(0.101)	(0.101)
Vehicle size (m^2)	1.341***	0.021	-0.503**	-0.517*	-0.504	-0.319	-0.276	-0.305
	(0.202)	(0.231)	(0.252)	(0.265)	(0.488)	(0.498)	(0.482)	(0.498)
Vehicle size*Income(¥10,000)	-0.111***	0.072**	0.147***	0.153***	0.065	0.039	0.033	0.025
	(0.024)	(0.031)	(0.035)	(0.038)	(0.104)	(0.104)	(0.102)	(0.106)
Power/Weight (kW/kg)	10.597***	11.885***	12.821***	12.743***	10.284***	7.829***	7.270***	7.925***
	(2.163)	(2.101)	(2.135)	(2.131)	(2.181)	(2.440)	(2.229)	(2.254)
Driving range (100km)	0.147***	-0.066*	-0.025	-0.009	0.114**	0.079*	0.071	0.082*
	(0.038)	(0.040)	(0.039)	(0.040)	(0.047)	(0.047)	(0.046)	(0.048)
Driving range*No. of charging ports (1,000)	-0.026***	-0.022***	-0.010*	-0.015***	-0.010	-0.002	-0.001	-0.024
	(0.010)	(0.008)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.018)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.500	0.556	0.564	0.567	0.564	-0.100	-0.103	-0.101
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						567.518	207.431	13.495
Underidentification stat						59.327	92.367	39.024
Weak Identification stat						567.518	207.431	13.495
Overidentification stat						0.000	22.072	22.629

Notes: The regressions are based on 150 cities. The dependent variable is ln(sales). Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for price, the number of charging ports and the interaction between subsidy and charging ports using central subsidy, battery capacity, lagged institutional EV stock and the interaction between subsidy and lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Nonlinear Effects base on Full Sample: Semi-log

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV	(7) IV	(8) IV
Consumer price (in ¥10000)	-0.072***	-0.070***	-0.074***	-0.074***	-0.067***	-0.146***	-0.157***	-0.158***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.029)	(0.023)	(0.023)
No. of charging ports (1,000)	0.042	0.009	0.166***	0.223***	0.227***	0.226***	0.226***	0.201***
	(0.062)	(0.050)	(0.062)	(0.064)	(0.067)	(0.066)	(0.066)	(0.070)
Square of no. of charging ports (1,000)	-0.214	-0.108	0.157	-0.865	-0.949	-0.937	-0.935	-0.020
	(1.756)	(1.491)	(1.328)	(1.213)	(1.272)	(1.266)	(1.266)	(1.657)
EV exempt from driving restriction	0.427***	0.459***	0.116	-0.010	0.036	0.032	0.031	-0.027
	(0.120)	(0.129)	(0.183)	(0.143)	(0.153)	(0.149)	(0.148)	(0.156)
Green plate for EVs	0.247***	0.132**	0.190***	0.307***	0.317***	0.314***	0.313***	0.316***
	(0.055)	(0.056)	(0.062)	(0.076)	(0.079)	(0.079)	(0.079)	(0.082)
Vehicle size (m^2)	0.525***	0.449**	0.370**	0.392**	-0.191	-0.112	-0.101	-0.162
	(0.185)	(0.179)	(0.185)	(0.189)	(0.182)	(0.182)	(0.176)	(0.181)
Power/Weight (kW/kg)	8.622***	11.561***	12.612***	12.492***	10.145***	7.330***	6.944***	6.932***
	(2.041)	(2.068)	(2.119)	(2.119)	(2.076)	(2.361)	(2.165)	(2.168)
Driving range (100km)	0.131***	-0.037	-0.012	-0.006	0.149***	0.105**	0.099**	0.100**
	(0.038)	(0.035)	(0.037)	(0.038)	(0.047)	(0.048)	(0.047)	(0.047)
Observations	25003	25003	24995	24994	24828	24828	24828	24493
Adjusted R^2	0.494	0.553	0.563	0.565	0.563	-0.103	-0.105	-0.105
City-Model FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	Y	N	N	N	N	N
City-Year FE	N	N	Y	Y	Y	Y	Y	Y
Cluster-Time FE	N	N	N	Y	Y	Y	Y	Y
Cluster-Brand-Year FE	N	N	N	N	Y	Y	Y	Y
Joint-F on excluded IVs						557.653	268.090	24.607
Underidentification stat						55.610	89.544	62.537
Weak Identification stat						557.653	268.090	24.607
Overidentification stat						0.000	22.135	21.724

Notes: The regressions are based on 150 cities. The dependent variable is ln(sales). Column (6) instruments price using central subsidy while column (7) instruments price using central subsidy and battery capacity. Column (8) instruments for price, the number of charging ports and the square of number of charging ports using central subsidy, battery capacity, lagged institutional EV stock and square of lagged institutional EV stock. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$