# Effects of Subsidies and Vehicle Restriction Exemptions on Electric Vehicle Adoption:

## Evidence from 87 Cities in China

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**Abstract**

This paper examines the effects of subsidies and exemptions from license plate quotas and driving restrictions on electric vehicle (EV) adoption in China. The analysis leverages spatial and temporal variations in national and local EV subsidies using a panel fixed-effects model based on monthly passenger vehicle registration data from 87 Chinese cities from 2016 to 2019. In addition, this study exploits the differential local exposure to a 2017 shift in the national subsidy policy using a difference-in-differences model. The results show that subsidies have positive but heterogeneous effects on EV adoption. Subsidies are most effective in first-tier cities, with a 10,000 RMB increase in subsidies being associated with an 18.77% increase in the EV market share. However, within the same city tier, subsidies are less effective in regions with higher GDP per capita and greater shares of government expenditure allocated to education or environmental protection. Additionally, exempting EVs from driving restrictions and license plate quotas is highly effective in promoting EV adoption. For instance, exemptions from license plate quotas increase EV market shares by over 220%. More specifically, a one percentage point increase in the probability of winning a lottery or a 1,000 RMB increase in the auction price for a conventional vehicle license plate is correlated with a 1.2% to 1.4% increase in EV market share. Results from the difference-in-differences analysis also support the conclusion that the effect of subsidies on EV adoption is positive.

JEL classification: L98, Q55

Key Words: electric vehicles, subsidy, vehicle restriction, difference-in-differences

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# 1 Introduction

Electric vehicles (EVs), including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs),[1] have become increasingly popular due to characteristics such as lower or even zero tailpipe emissions, as well as reduced reliance on fossil fuels. Deploying EVs has been widely regarded as a promising way of rapidly reducing air pollution in densely populated areas and decarbonizing the transportation sector (IEA, 2020).[2] Global sales of EVs in the passenger light-duty vehicle segment have increased rapidly in recent years. According to the IEA (2020), from 2014 to 2019, the average annual growth rate of global electric cars was 60%, reaching 7.2 million vehicles in 2019. Notably, EVs in China accounted for 47% of the global stock in 2019.

The Chinese central government started introducing policies to promote the development of EVs[3] in 2009. These policies include subsidies for the research and development (R&D), production, and purchase of EVs. Such incentives are designed to achieve four goals: 1) have China become one of the leading countries in the global automobile industry; 2) reduce the economy's dependence on imported crude oil; 3) improve urban air quality; and 4) reduce carbon emissions that contribute to climate change. The number of EVs in China has sharply increased over the past decade. In 2018, around 1.5 million passenger EVs were sold in China, accounting for over half of all global sales.

Among the policy incentives provided by governments around the world, monetary subsidies are the most popular. The central government in China started providing a subsidy to private EV buyers nationwide in January 2016 and planned to phase it out by June 2019. On top of the national subsidy, many local governments provide matching subsidies, ranging between 10% to 106% of the national subsidy. In total, the national and local subsidies can be as high as 110,000 RMB (roughly, $16,400).

With the burgeoning EV market in China and the considerable investments promoting EVs, it is essential to examine the effectiveness of these subsidies. This paper focuses on the subsidies for private EV buyers, including both national and local subsidies. By exploiting the spatial and temporal differences in the subsidies, this paper examines the relationship between subsidies and EV adoption using a fixed effects panel regression analysis. The main

[1] The term EVs include BEVs, PHEVs and fuel cell electric vehicles (FCEVs). This study focuses on BEVs and PHEVs which are fueled with electricity from the grid, so EVs in this study only refer to BEVs and PHEVs.

[2] In 2020, the transport sector accounted for nearly one-quarter of global energy-related $CO_2$ emissions.

[3] In China, EVs are also referred to as new energy vehicles (NEVs), which also include BEVs, PHEVs and FCEVs.

results show that subsidies have positive effects on EV adoption. However, these effects are heterogeneous across cities. Using a well-known ranking system that groups cities into five tiers based on their economic and financial environments,[4] the results show that private buyers in first-tier cities are the most responsive to the subsidies: A 10,000 RMB increase in subsidies leads to an 18.77% average increase in EV market share.[5] Furthermore, lower GDP per capita and smaller shares of government expenditure allocated to education or environmental protection both enhance the positive effect of subsidies on EV adoption.

Besides providing subsidies, exempting EVs from license plate registration quotas and driving restrictions[6] are important factors that influence their adoption. Results show that exemptions from license plate registration quotas and driving restrictions are, on average, associated with over 220% and about 30% increases in EV market shares, respectively. Notably, having a license plate registration quota exemption is equivalent to a subsidy increase of over 117,000 RMB in the first-tier cities. In addition, this paper further explores the quantitative relationship between these two vehicle restrictions and EV adoption. The results show that a one percentage point increase in the probability of winning a lottery or a 1,000 RMB increase in the auction price for a conventional vehicle license plate is correlated with a 1.2% to 1.4% increase in EV market share.

Furthermore, I estimate the effect of decreasing subsidies on EV adoption using a difference-in-differences (DID) model. On December 30, 2016, the central government announced that, starting in 2017, local subsidies must not exceed 50% of the national subsidy. This policy capped local subsidies and has led to a reduction of 4 to 50 percentage points in local-to-national subsidy percentages[7] across cities whose local subsidies were over 50% of the

[4]Cities are grouped into the first, second, third, fourth, and fifth tier, based on five dimensions: 1) concentration of commercial resources; 2) the extent to which a city serves as a commercial hub; 3) the vitality of urban residents; 4) the diversity of lifestyle; and 5) their future dynamism. First-tier cities are the top-ranking cities representing the most developed areas in China with the most affluent and sophisticated consumers, see: https://en.wikipedia.org/wiki/Chinese_city_tier_system. The ranking is reported by Yicai, one of the top media outlets focusing on economics and finance in China. This study combines the fourth and fifth tiers given that only small samples of these two tiers are included in the analysis.

[5]Market shares are also referred to as penetration rates.

[6]There are two kinds of restrictions on internal combustion engine vehicles (ICEVs) in China: limited license plate registrations and driving restrictions. EVs are exempt from these two vehicle restrictions. Seven cities and one province have adopted license plate registration quotas (see details in Section 3.3), which aim to control the growth of ICEVs by applying quotas to the supply of license plates for ICEVs. The license plate registration quotas only apply to the ICEVs, with the exception of Beijing, which also has quotas for EVs' license plates. In addition, several cities have started to restrict when and where ICEVs are allowed to be driven within the inner cities.

[7]Local-to-national subsidy percentage is defined as the ratio of local to national subsidy expressed as a fraction of 100, e.g., a local-to-national subsidy percentage of 50% indicates that the ratio of local to national subsidy is 0.5:1.

national subsidy prior to the policy change. Results of the DID model show that the sudden reductions in local subsidies significantly slowed down EV adoption in the affected cities, providing evidence for the positive relationship between subsidies and EV adoption.

As EVs have become popular worldwide, and researchers have started to investigate the factors influencing EV adoption. Many previous studies relied on survey data, due to the limited temporal coverage of available EV sales data (Carley et al., 2013; Langbroek et al., 2016). More recent empirical studies have started to use EV sales or registration data. Researchers have generally found that financial incentives have positive effects on EV adoption. However, results for non-financial incentives are mixed (Clinton and Steinberg, 2019; Wee et al., 2018).

Studies have increasingly focused on the EV market in developing countries, especially China. Some studies show that subsidies and tax exemptions significantly promote EV adoption (Ma et al., 2017; Li et al., 2019, 2022), while others find non-significant subsidy effects (Wang et al., 2017; Qiu et al., 2019). As for non-financial incentives, investment in electrical charging facilities and discounts on charging have had positive effects on EV adoption (Wang et al., 2017; Qiu et al., 2019; Li et al., 2022), while parking benefits do not appear to have significant effects (Qiu et al., 2019; Wang et al., 2017). Furthermore, the two aforementioned restrictions on ICEVs, driving restrictions and license plate quotas, have been found especially influential, sometimes having the largest impact on EVs adoption (Ma et al., 2017; Wang et al., 2017; Li et al., 2022).

This paper contributes to the existing literature in several ways. First, existing research mostly relies on survey data, or EV sales data that are limited to a few time periods and cities or regions. This paper shares similarities with Li et al. (2022) regarding the data and the baseline analysis.[8] Li et al. (2022) uses quarterly EV sales data from 2015 to 2018 across 150 Chinese cities, while this study employs monthly EV registration data from 2016 to 2019 across 87 Chinese cities[9] and an original data set of local policy incentives. Although Li et al. (2022) uses quarterly EV sales, their data contains more information about vehicle attributes, such as brand, model, and driving range. Nevertheless, without vehicle attributes, the more granular monthly data used in this analysis still allows for accurate estimation of

[8] This analysis started in early 2020 before Li et al. (2022) published their study. The baseline results of this paper are consistent with that of Li et al. (2022). In addition, this paper takes into account the effect of license plate quota policy and further examines it by using two variables to denote lottery and auction separately. Besides, this paper also differs from their study in terms of heterogeneous effects analysis and in the identification strategy.

[9] The sampled cities are chosen because they all participated in the pilot program to promote EVs before 2016. This sample covers not only the top-tier and well-developed cities but also third and fourth-tier cities.

the effects of EV policies at the city level.

Another distinguishing feature of this study is that it not only considers the effects of subsidies and other incentives, but also examines the heterogeneous effects of subsidies. My findings show that the magnitude of the subsidy effects varies across cities in different tiers, and is larger for cities with a lower GDP per capita and smaller shares of government expenditure allocated to education or environmental protection.

Furthermore, this paper exploits the event of an unexpected reduction in subsidies for some of the sampled cities, as the result of a national policy shift in 2017. Applying the difference-in-differences method, this study investigates the effects of the sudden decrease in local EV subsidies. The difference-in-differences results provide supplementary evidence that subsidies promote EV adoption.

The remainder of this paper is organized as follows. Section 2 reviews existing studies on the factors influencing EV adoption, mainly focusing on policy incentives. Section 3 summarizes the relevant policies, including the EV subsidy policies, driving restrictions, and license plate registration quotas. Section 4 describes the data. Section 5 discusses the specifications and identification strategy. The results and robustness checks are presented in sections 6 and 7, respectively. Conclusions, study limitations, and future research directions are presented in section 8.

## 2 Literature Review

This review focuses on the factors influencing EV adoption. Due to EVs being a relatively new technology and there being limited time available to collect the actual EV sales data, this review includes both econometric analyses and studies using consumer survey data. Coffman et al. (2017) categorizes the factors influencing EV adoption into three groups: 1) internal factors, 2) external factors, and 3) policy mechanisms.

The internal factors refer to vehicle ownership costs and unique characteristics of EVs, such as driving range and charging time. This paper does not address the problems related to internal factors and instead focuses on the external factors and policy mechanisms.

The external factors include fuel prices, charging networks, consumer characteristics, public visibility and social norms. Empirical research has produced mixed results on external factors. Sierzchula et al. (2014) finds that relative fuel prices appear to have a non-significant impact on EV adoption, whereas studies by Gallagher and Muehlegger (2011) and Diamond (2009) both find annual fuel savings or gas prices have a significant and positive impact.

Although the usage costs of EVs would be lower as the relative fuel prices increase, survey studies conducted by Caperello and Kurani (2012) and Turrentine and Kurani (2007) show that consumers lack the knowledge necessary for calculating the actual operational expenses of driving a vehicle. Jaffe and Stavins (1994) states that consumers make purchase decisions based on rules of thumb and therefore focus primarily on the purchase price without having a clear idea of the operating expenses (Levine et al., 1995). The impact of charging facilities also varies across empirical studies. Mersky et al. (2016) finds that the number of available charging facilities has the highest predictive power for BEV sales and Slowik and Lutsey (2017) identifies charging infrastructure as one of the significant predictors of EV adoption in the United States. However, Wee et al. (2018) fails to find significant evidence for the impact of public charging facilities using a data set including all 50 states of the United States.

EV adoption could also be correlated with socio-demographic variables. On the one hand, Nayum et al. (2016) suggests that early EV adopters are typically highly educated, have higher incomes, are relatively young, and tend to live in larger, multi-car households. On the other hand, Hidrue et al. (2011) finds that income and owning multiple cars are not important factors influencing a person's likelihood of purchasing an EV. As for social norms or psychological factors, survey studies find the early EV adopters have pro-environmental attitudes (Wolf and Seebauer, 2014) or follow an environment-oriented lifestyle (Axsen et al., 2016). Additionally, people have a more positive attitude towards EVs if they are more interested in new technologies and engage in a technology-oriented lifestyle (Wolf and Seebauer, 2014; Axsen et al., 2016). However, Sierzchula et al. (2014) finds that all these socio-demographic and environment-related factors are not significant in predicting EV adoption.

To investigate the effects of consumer-oriented government policies on EV adoption, researchers generally divide governmental incentives into financial and non-financial ones. Some studies further differentiate between one-time financial incentives (such as subsidies or rebates) and recurring financial incentives that reduce usage costs (such as exemptions from circulation taxes or subsidies for charging fees). The most common financial incentives are purchase subsidies, which are widely provided around the world. Typical non-financial incentives offered by governments are access to special lanes or restricted traffic zones and free or preferential parking. In general, past research has found positive and significant effects of one-time financial incentives but ambiguous outcomes for both recurring financial and non-financial incentives.

Gallagher and Muehlegger (2011) uses U.S. data between 2000 and 2006 and shows that tax incentives have significant and positive effects on hybrid electric vehicle adoption, although the magnitude of the effects varies based on the type of tax incentive. In their study, sales tax waivers induce a more than ten-fold increase in hybrid sales compared to income tax credits. Clinton and Steinberg (2019) also finds significant and positive effects of direct purchase rebates but non-significant effects of income tax credits on BEV adoption. Similarly, the results presented by Wee et al. (2018) show that subsidies have significant effects on EV adoption, while non-financial incentives do not. These results also generalize to countries other than the United States. Ma et al. (2017) employs sales data across six major cities in China from 2011 to 2016 to find positive relationships between EV market shares and both subsidies and tax exemptions. Li et al. (2022) analyzes quarterly data across 150 Chinese cities from 2015 to 2018 and find that subsidies account for over half of all EV sales. Sierzchula et al. (2014) uses 2012 EV adoption rates in 30 countries to find that financial incentives have a positive and significant influence on EV sales. Münzel et al. (2019) uses 2010 to 2017 plug-in electric vehicle sales data from 32 European countries to find similar results. In contrast, non-financial incentives are deemed to have a non-significant impact in a study by Mersky et al. (2016) who uses data from Norway.

Besides access to special lanes and parking benefits, there are two other non-financial policy instruments important to the Chinese EV market, namely exemptions from driving restrictions and license plate registration quotas. Survey studies conducted in China by both Qian et al. (2019) and Zhang et al. (2018) have found that exempting EVs from the license plate registration quotas is one of the most influential factors in promoting EVs. Indeed, Qian et al. (2019) reports that the average Chinese consumer is willing to pay more than 10,000 RMB for EVs to get a free vehicle license. Prior empirical studies on actual EV sales show that a positive relationship exists between EV adoption and exemptions from these two restrictions. For example, Ma et al. (2017) finds that the two exemptions are among the factors that promote EV adoption. Wang et al. (2017) also finds that the exemption from driving restrictions is one of the four most important factors influencing adoption, besides the density of chargers, the exemption from license fees, and prioritizing charging infrastructure when assigning construction land.

Although a large proportion of studies have found that EV subsidies and other financial incentives are significant factors promoting EV purchases, some research has shown that this is not always the case. Diamond (2009) employs U.S. data from the 2001 to 2006 hybrid electric vehicle market and failed to find any significant impact of monetary incentives. Wang et al. (2017) analyzes EV sales across 41 cities in China from 2013 to 2014 and found no significant effects from subsidies, though this could be due to lack of variation in subsidies among the cities examined by the authors. Empirical research by Qiu et al. (2019), on 88 pilot cities in China from 2014 to 2015, indicated that EV subsidies played no significant role in EV adoption. Additionally, Wang et al. (2019) explores factors influencing EV market shares in 30 countries during 2015 and finds that fiscal incentives were not the reason for the differences in EV adoption rates across countries. However, it is worth noting that these studies either focus on the early stages of the EV market or have rather restricted time windows. One of the possible reasons for the ineffectiveness of these incentives is that people may not be aware of the incentives and of new technologies, which could result in low adoption (Krause et al., 2013).

Some studies have examined the heterogeneous effects of financial incentives. Studies using sales data and consumer surveys indicate that the effectiveness of policy incentives may depend on the magnitude of the incentives and consumers' psychological characteristics. Jenn et al. (2013) compares financial incentives above and below $1000, and only finds a statistically significant impact of the higher financial incentives. This suggests that, in order to yield an effect on hybrid electric vehicle sales, the incentive needs to be sufficiently high. Jenn et al. (2018) uses the number of articles that are related to the incentives to operationalize consumer awareness of EV purchase incentives. Their study shows that raising consumer awareness increases the incentive effects. Ye et al. (2021) exploits both qualitative and quantitative data to analyze the combined effects of psychological and policy attributes. The authors conclude that an absence of pro-EV attitudes, subjective norms, and perceived behavioral control results in lower EV purchase intentions, despite existing EV subsidies from the government.

By exploring survey data from Austria, Priessner et al. (2018) has also found that psychological and socio-demographic factors play an important role in predicting EV adoption. They find that people with some types of psychological characteristics, such as more individualistic and less egalitarian people, are less likely to respond to various types of policy incentives. Langbroek et al. (2016) concludes that the effects of policy incentives tend to differ between categories of drivers, and people that are further in the process of behavioral change will be more responsive to the policy incentives. Helveston et al. (2015) conducts survey studies in China and the United States, and the results shows that, with comparable subsidies, there are substantial differences in the impact of subsidies on BEV shares between these two countries, which are caused by differences in consumers' preferences.

# 3 Summary of Policies

## 3.1 National Policies for EVs

In China, national policies promoting EVs can be divided into three phases (Wu et al., 2021). In the first phase, the central government selected several pilot cities to provide financial support for EVs in the public sector, such as for electric buses or electric delivery trucks. This program was gradually extended to cover more cities as well as to include private EV buyers in five cities. In the second phase, the subsidy programs for private EV buyers were expanded to 88 cities, where some of the regional governments also started to offer additional local subsidies. In the last phase, which spanned the period from 2016 to July 2019, the central government provided every private EV buyer with a national subsidy, while more local governments joined to provide local subsidies of varying amount. At the start of 2017, the central government set an upper bound for local subsidies, restricting local governments from offering additional purchase subsidies that were larger than 50% of the national subsidy.

- **Phase I (2009-2012)**[10]

In 2009, the central government issued the "Automotive Industry Readjustment and Revitalization Plan" and the "Notice on New Energy Vehicle Demonstration and Subsidies".[11] The central government began subsidizing public-sector purchases of EVs in 13 cities, carrying out the "Ten Cities, Thousands of NEVs" program. In 2010, the program was extended to 25 cities. The EV-promoting program called for the production of 500,000 electric vehicles (5% of the total vehicle sales) by 2011,[12] while providing subsidies for EVs (as high as 60,000 RMB for a BEV and 50,000 RMB for an advanced PHEV).

In terms of subsidies for private buyers, an initial program was announced in late 2010 which would provide subsidies to private buyers in five pilot cities (Changchun, Hangzhou, Hefei, Shanghai, Shenzhen),[13] this program was later expanded to also include Beijing. The subsidy was given to the EV manufacturers/sellers, who were asked to deduct the subsidy from the vehicle price before selling it.

- **Phase II (2013-2015)**

[10] Mainly from Howell et al. (2014).

[11] "Energy saving and new energy vehicle demonstration temporary subsidy extension". In China, EVs are also referred to as new energy vehicles (NEVs).

[12] Only about one-third of the original goals had been achieved by October 2011; the government later pushed the deadline for achieving this target to 2015.

[13] All of them are home to the headquarters of some of the largest Chinese automakers.

Policies in Phase II added more regions to those already covered in Phase I. In September 2013, the Ministry of Industry and Information Technology (MIIT), the Ministry of Science and Technology (MST), the Ministry of Finance (MOF), and the National Development of Reform Commission (NDRC) jointly issued the financial subsidy policies for the EV industry, and the financial subsidy was extended to 88 cities, including a city-level county, Pingtan.[14] EV sales increased rapidly after 2015, largely as a result of the extensive financial support and improvement of EV related infrastructure as well as the improved performance of EVs. However, problems such as adverse selection and fraud emerged in a few places.[15] Thus, the central government started tightening the eligibility criteria for EV subsidies and emphasizing the innovation of EV technology (Wu et al., 2021).

- **Phase III (2016-2020)**

In mid-2015, the central government issued a document stating that it would provide subsidies to private buyers nationwide starting in 2016.[16] Private buyers were able to receive national purchase subsidies regardless of the city in which they purchased the EV. The subsidies were supposed to decline every year[17] and be completely phased out by the end of June 2019. However, they were resumed and extended in April 2020 with the goal of alleviating the negative impacts of COVID-19. Details on the national subsidy are displayed in Figure 3 in the following section.

On December 30, 2016, the central government announced an adjustment of the subsidy policy and set a limit on the maximum local subsidy that can be received in addition to the national one ($\leq$50% of national subsidy).[18] The new restriction on the local subsidy is exploited by using the difference-in-differences methodology. On February 13, 2018 the central government issued another adjustment – subsidizing the expansion of charging facilities.

## 3.2 Local Policies for EVs

Local governments mostly employed a version of the national subsidy scheme, using driving range as the main criterion for setting local subsidy rates (see detailed categories for subsidies

[14] This paper focuses on 87 cities of the 88 cities due to the lack of demographic data for Pingtan.

[15] In 2015, four EV manufacturers were found to register EVs and apply for subsidies without actually producing the vehicles; this has been reported on the news: http://www.gov.cn/xinwen/2016-09/09/content_5106700.htm

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

[17] The driving range requirements for subsidies were increasing every year.

[18] Source: http://www.miit.gov.cn/n1146295/n1652858/n1652930/n3757018/c5449722/content.html

based on driving range in Figure 3). Many local subsidies were set to be a proportion of the national subsidy, such as 50% or 100% (in the policy documents, these are usually referred to as 0.5:1 and 1:1 matches). In this paper, although following the same subsidy structure, some cities set up additional requirements. For instance, in 2016, Hefei offered a larger local subsidy (equivalent to 100% of the national subsidy) for BEVs that exceed the 150km driving range and a smaller one (equivalent to 20% of the national subsidy) for the other EVs.[19] In 2017, Hangzhou differentiated EVs based on their size, offering a smaller local subsidy (equivalent to 25% of the national subsidy) to mini-BEVs and a larger one (equivalent to 50% of the national subsidy) to all others.[20] Similarly, in 2017, Wuhan gave a local subsidy equivalent to 50% of the national subsidy to EVs that had a wheelbase of over 2.2 meters and a local subsidy equivalent to 20% of the national subsidy to those that did not. Other cities set their own subsidy amount rather than matching a proportion of the national subsidy, such as Shanghai in 2016 and 2017,[21] Wuhu in 2016,[22] and Xiangyang from 2016 to 2018.[23]

Some local governments also introduced a variety of other policy incentives for EVs adopters, such as extra subsidies for charging (facilities or electricity fees),[24] extra subsidies for specific groups of people who switch to EVs (like taxi drivers and high-pollution ICEVs owners), free parking or reduced parking fees, and exemptions from restrictions on ICEVs (see the following sections 3.3 and 3.4).

## 3.3 License Plate Registration Quotas

License plate registration quotas are government interventions to control the number of cars by limiting the supply of license plates (mainly ICEVs), aiming to mitigate traffic congestion and air pollution. Under a license plate registration restriction, a city government sets up a license plate quota for a whole year, whereby license plates are obtained each month (or every two months) through either a lottery, an auction, or both.

There are in total seven cities (Shanghai, Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou,

[19] Source: https://www.d1ev.com/news/zhengce/47595

[20] Source: http://www.hangzhou.gov.cn/art/2017/8/14/art_1302334_4131.html

[21] Source: https://www.d1ev.com/news/zhengce/42837

[22] Source: http://www.cbea.com/cyzc/201812/427165.html

[23] Source: https://www.d1ev.com/news/zhengce/48035; https://www.d1ev.com/news/zhengce/60299; https://m.evpartner.com/news/detail-41084.html

[24] A few cities offered extra subsidies for private charging facility installations or electricity fees (see Table 17). However, most of the policies for charging facilities were government investments in building public charging facilities, which are not directly included in this paper, although their effects should be reflected in the number of charging facilities.

Shenzhen) and one province (Hainan province) that have implemented license plate registration quotas.[25] All seven cities implemented these restrictions before 2016, the start of the period of interest for this study. Hainan province[26] introduced the restriction in August 2018. Shanghai has only adopted an auction system to distribute the ICEV license plates, whereas Beijing, Guiyang,[27] and Hainan have only used lottery systems. The other four cities (Guangzhou, Tianjin, Hangzhou, and Shenzhen) have adopted both.

To my knowledge, there does not exist a centralized database on the auction and lottery results for license plate quota policies. Therefore, I collected the monthly average auction price[28] as well as the probability of winning a lottery[29] for an ICEV license plate from government announcements and news articles. The auction price and probability of winning a lottery for a ICEV license plate reflect how hard it is for an ICEV buyer to obtain a license plate.

The bidding price on a license plate for an ICEV is quite high in regions that have the auction option, with the average purchase price in an auction ranging from 15,461 to 95,103 RMB. In the lottery system, although ICEV buyers do not need to pay high prices for license plates, they generally have to wait for a long time given the extremely low probability of winning a lottery. The average probability of winning a lottery are mostly below 1%, with Hainan being an exception (14.2% average probability of winning a lottery in 2019).[30] EVs are exempted from the restrictions in all cities except Beijing, where PHEV buyers are required to enter the same lottery for ICEV buyers, and BEV owners need to enter a separate lottery (with a higher probability of winning) to get a license plate.[31] Therefore, car buyers

[25] Another city, Shijiazhuang, has a different type of restriction on license plate registration. It restricts each household from buying a third personal passenger car. Since it is not common for a household in China to purchase more than two cars, this city was not included in the list of cities having license plate registration quotas.

[26] In this study, only one city, Haikou, is in Hainan province.

[27] In Guiyang, the lottery was for special license plates that were allowed to enter the first ring road from 7 a.m. to 9 p.m. (including holidays). This lottery policy was abolished in September, 2019.

[28] Source: Guangzhou: http://jt.gz.bendibao.com/news/2015427/186209.shtml; Hangzhou: http://jj.hzqcjj.com/bidsite/app/bidIssue/manage; Shanghai: http://www.yunpaiwang.net/jiagezoushi/; Shenzhen: http://sz.bendibao.com/jt/2016718/775782.htm; Tianjin: http://xkctk.jtys.tj.gov.cn/ggl1/.

[29] Source: Beijing: https://xkczb.jtw.beijing.gov.cn/jggb/index_12.html; Guangzhou: http://jt.gz.bendibao.com/news/2015527/188730_2.shtml; Guiyang: http://gy.bendibao.com/live/2018627/43486.shtm and other news articles; Haikou: https://www.hnjdctk.gov.cn/tzgg/index_8.html; Hangzhou: https://hzxkctk.cn/tzgg/index_31.html; Shenzhen: http://sz.bendibao.com/jt/2017829/796316.htm; Tianjin: http://www.bitenews.cn/jgcx/tjcx/279.html and other news articles.

[30] The different methods (lottery, auction, or a mix of both) applied by each city's government, and the costs or probability of getting a license plate are well summarized by Chi et al. (2021).

[31] In Beijing, the lottery process for a license plate for a BEV is only available to car-free families. Source: https://auto.ifeng.com/quanmeiti/20190905/1326967.shtml

have incentives to switch from conventional ICEVs to purchasing EVs, especially those in great need of vehicles but who cannot afford the extra costs for obtaining license plates, or do not want to wait for a long time in the lottery system.

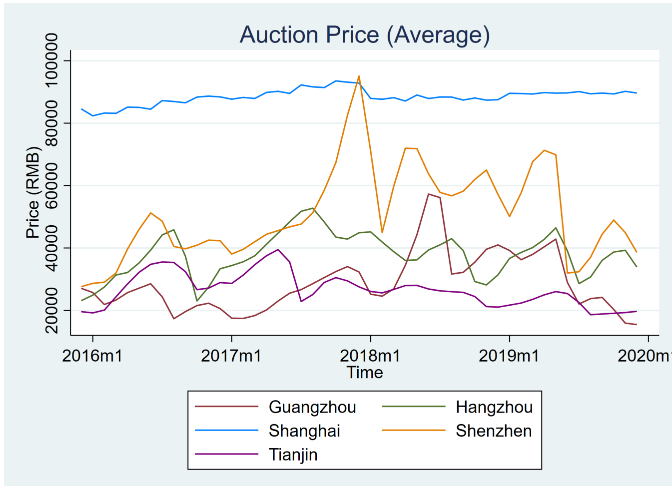
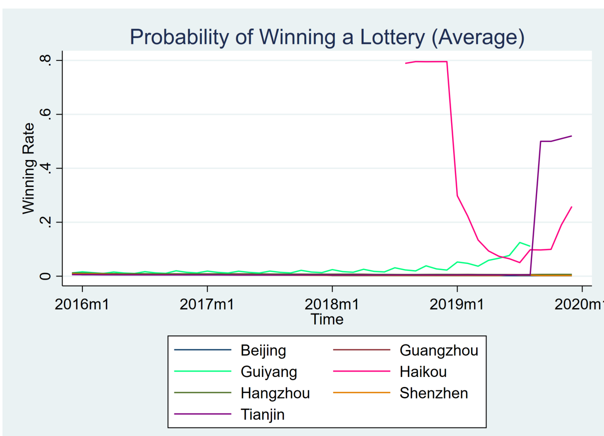
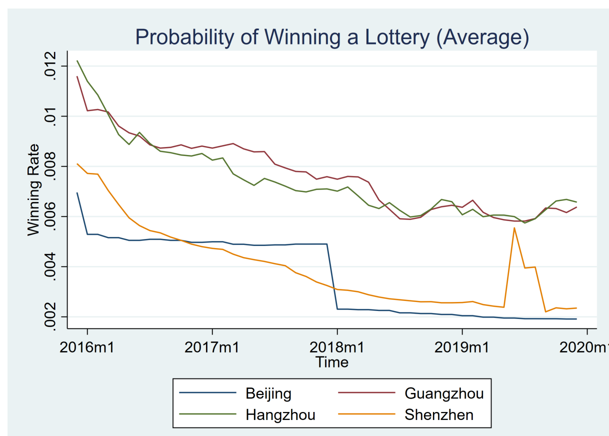



Figure 1: The Average Auction Price of an ICEV License Plate




(a) All Cities




(b) Zooming in on the Four Cities with Relatively Low Probabilities

Note: Haikou (in Hainan province) started the license quota policy in August 2018.

Figure 2: The Average Probability of Winning a Lottery for an ICEV License Plate

Figure 1 displays the average auction price of an ICEV license plate in five cities that use auction systems to distribute the license plates. Figure 2(a) presents the average probability of winning a lottery for seven cities that use lottery systems to distribute the license plates for ICEVs, while figure 2(b) zooms in on the four cities with relatively low probability of winning a lottery. The figures reveal that there can be considerable differences across cities with the same license quota policy. For instance, an ICEV buyer would need to pay over 80,000 RMB in Shanghai in order to get a license plate, but less than 40,000 RMB in Tianjin.

### 3.4 Driving Restrictions

Driving restrictions refer to regulations imposed on ICEVs or specific groups of vehicles, usually defining when and/or where the vehicles can be driven. The Beijing Municipal Government first imposed a driving restriction during the Olympic Games in 2008 to mitigate traffic congestion and air pollution. The policy at the time restricted cars with license plate numbers ending with odd and even digits from being driven on alternate days during that period. After the 2008 Olympic Games, the government continued the regulation after some adjustment, restricting two numbers each workday based on the last digit on the license plate. Later, other city governments also started to introduce various types of driving restrictions on ICEVs to address traffic congestion and air pollution caused by the rapidly growing number of vehicles on the road in urban areas.

I compiled a dataset containing information about the driving restrictions in the sampled cities from government policy documents and news articles. The information consists of starting and ending dates of the driving restrictions, if there are any. In addition, I also categorized the driving restrictions into five groups.

Among the 87 cities in the dataset, 32 had implemented some kind of driving restriction, including temporary or seasonal restrictions, by 2019. Table 1 displays the numbers of cities in different driving restriction groups from 2016 to 2019.

| $DR$ | Group | Description | Year 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| 0 | Group 0 | No restriction at all | 72 | 66 | 58 | 55 |
| | Group 1 | Temporary restriction or seasonal restriction | 3 | 5 | 5 | 6 |
| 1 | Group 2 | Restriction implemented approximately four times a month | 6 | 10 | 17 | 18 |
| | Group 3 | Restriction implemented approximately 6-7 times a month | 1 | 1 | 1 | 2 |
| | Group 4 | Restriction implemented half of the time | 3 | 3 | 4 | 4 |
| | Group 5 | Restriction implemented every weekday during rush hours | 2 | 2 | 2 | 2 |

Table 1: Number of Cities in Different Groups of Driving Restrictions

For the analysis in this paper, I combine the first two groups (Group 0, Group 1) into one, which is considered as having no driving restrictions (dummy $DR = 0$), and the remaining groups (Group 2, Group 3, Group 4, Group 5) into another one which is considered as having driving restrictions (dummy DR=1). By 2019, 26 cities have $DR$ equal to one, while the $DR$

for the remaining 61 cities remains zero throughout the sample period. Group 1 is included in the first category because cities in Group 1 only have temporary restrictions based on the weather/air quality conditions. It is therefore reasonable to assume those restrictions will not affect people's decision to buy an EV or not.

# 4 Data

Given the limitations on the EV registration data available,[32] the data used in this paper are from 2016 to 2019 (unless specified otherwise). The EV registration data after 2016 are relatively more reliable since national and local governments became stricter with the EV producers when assessing their eligibility for the subsidy due to the fraud cases uncovered in 2015.[33] From over 200 cities in China, 87 are chosen for this analysis. Those 87 cities were pilot cities in the program described in *Phase II* (see Section 3) and were used to promote EVs before 2016. Therefore, it is reasonable to assume that these cities were intent on promoting EV adoption, which means they would have put more effort into disseminating information on the relevant technologies and benefits of EVs. Additionally, these cities would be more likely to have planned or set up a certain level of EV charging facilities, which is key for encouraging people to start adopting EVs.

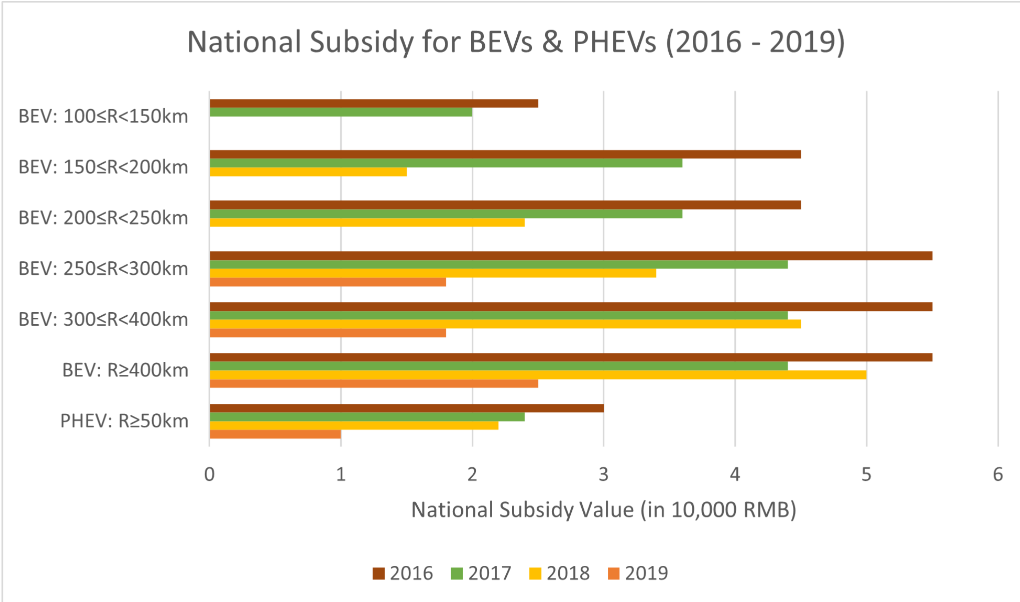
## 4.1 Subsidies

The central government provided subsidies to EV buyers following the scheme displayed below in Figure 3. The subsidies generally decreased over time, except for EVs with over 300 $km$ driving range, which were provided with a higher subsidy in 2018 compared to 2017.

In addition to the national subsidy, local governments offered additional subsidies to EV buyers. To my knowledge, there is no integrated dataset that covers and summarizes local EV subsidy policies in China. I collected and compiled a dataset that contains information on the amounts of local and national subsidies, as well as the local-to-national subsidy percentages (local subsidies as percentages of the national subsidy).

[32] Before 2016, fewer than 30 cities had EV registration data, and the data did not differentiate between EVs and fuel cell electric vehicles.

[33] In 2015, four EV manufacturers were found to register EVs and apply for the subsidy without ever producing the vehicles. This was reported in the news: http://www.gov.cn/xinwen/2016-09/09/content_5106700.htm. Based on the report: https://theicct.org/subsidy-fraud-leads-to-reforms-for-chinas-ev-market/, from 2013 to 2015, 8015 vehicles (around 2% of the total sales covered in the investigation) produced by 12 manufacturers were officially disclosed by the Chinese government have been involved in this scandal.




Note: "R" indicates driving range requirement for an EV to qualify for that specific subsidy.

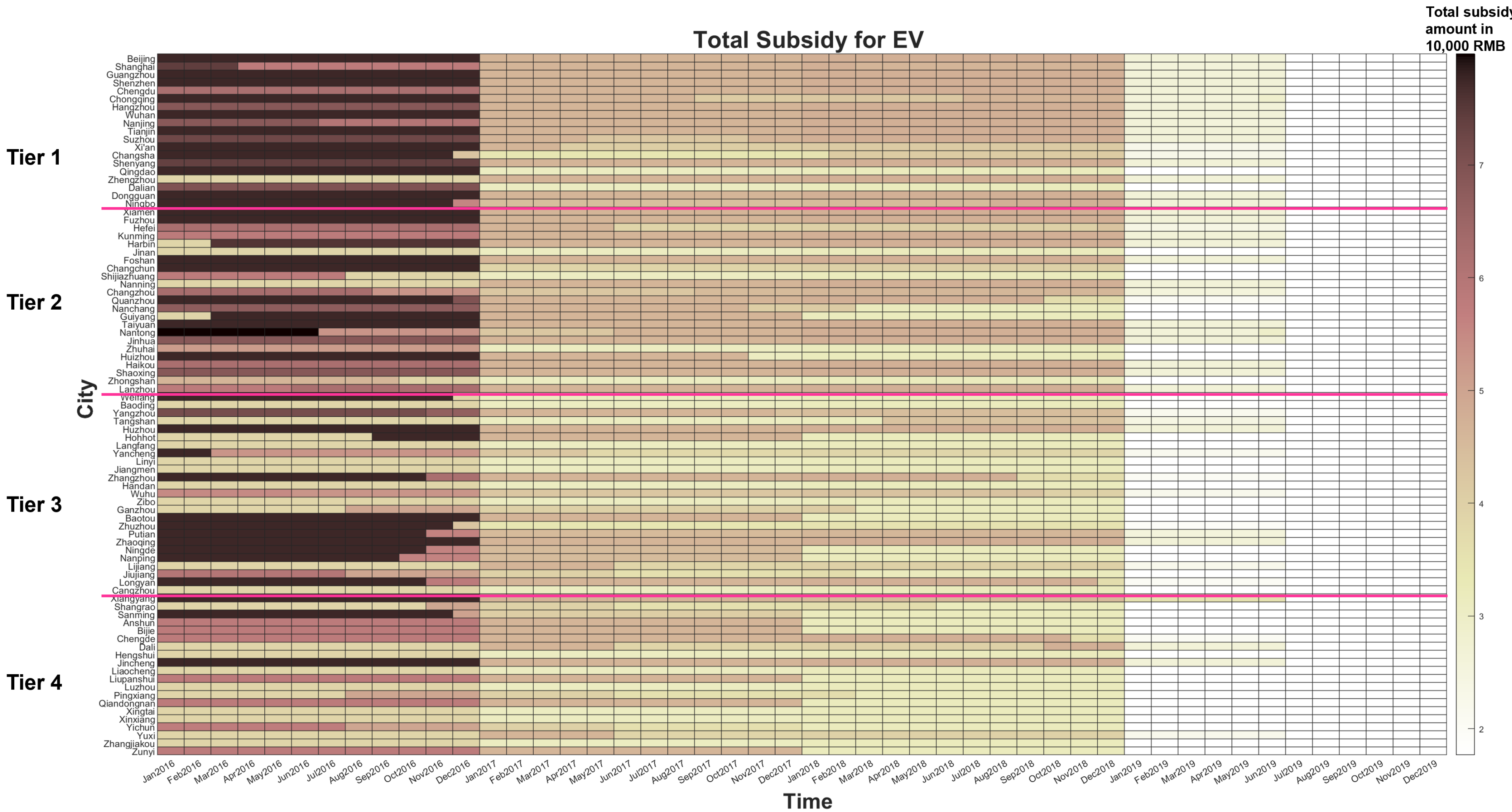
Figure 3: National Subsidies for Different Categories of EVs from 2016-2019, by driving range (R)

Figure 4 graphically shows the total subsidy amounts for EVs in the sampled cities from 2016 to 2019.[34] Cities are grouped into city tier 1, 2, 3, and 4, and the number of cities are distributed quite evenly across the different tiers. As mentioned in the introduction, the municipal tier ranking system is well-known in China and cities are categorized into different tiers based on their economic and financial environments.[35] Darker colors indicate higher amounts of the total subsidy. The figure reveals how subsidies vary on two dimensions: 1) Different cities may simultaneously offer different subsidies, while 2) the amount of the subsidies within the same city changes over time. In general, the subsidies were eventually phased out by the end of June 2019, according to the central government's plan.[36] Many local governments offered additional subsidies which were usually set up as proportions of the national subsidy. For instance, Beijing provided an additional local subsidy that was equal to 100% of the national subsidy in 2016. The local-to-national subsidy percentages for the sampled cities are graphically depicted in Figure 8. The figure also shows the abrupt decrease in the subsidy across about half of the sampled cities at the start of 2017. This was due to the announcement made by the central government on December 30, 2016, which

[34]The numbers are the average subsidies across different EV categories as shown in Figure 3 (including BEVs and PHEVs).

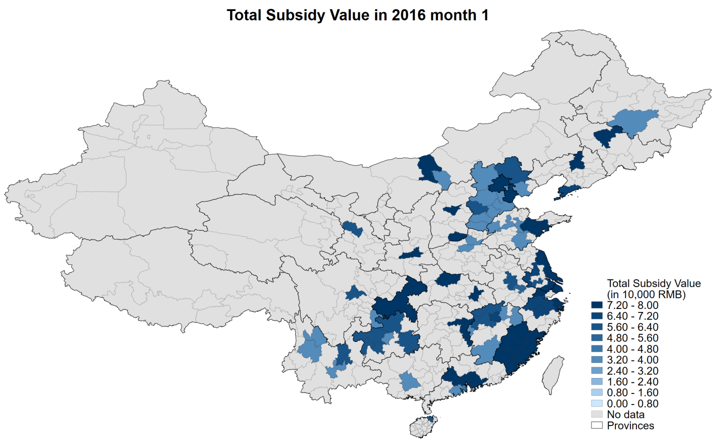
[35]The biggest and most well-developed cities are generally in the first tier; for instance, Beijing, Shanghai, Guangzhou and Shenzhen all belong to the first tier.

[36]Later, in 2020, the government resumed subsidy incentives hoping to promote automobile sales during the COVID-19 pandemic.

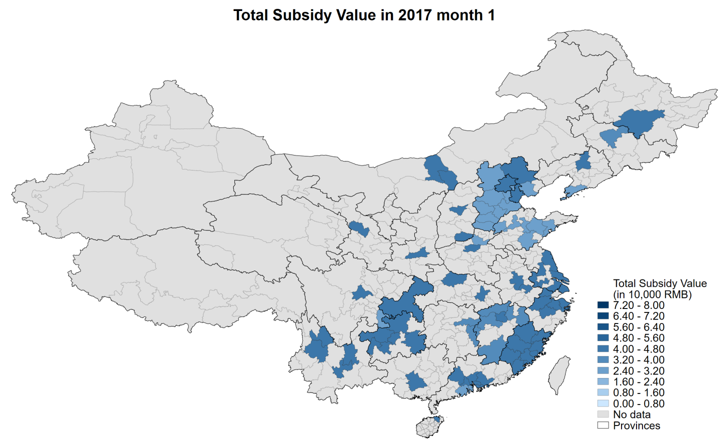



Note: A darker color implies a higher value of the total subsidy. Numbers along the legend bar on the right-hand side indicate the total subsidy (average value per vehicle) in 10,000 RMB.

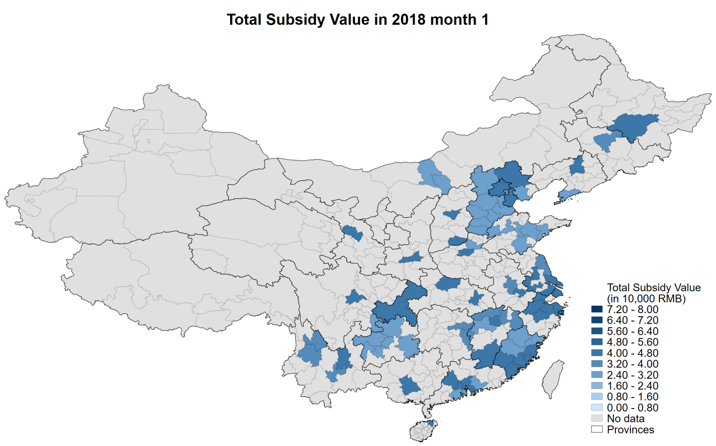
Figure 4: Total Subsidy Amounts for EVs



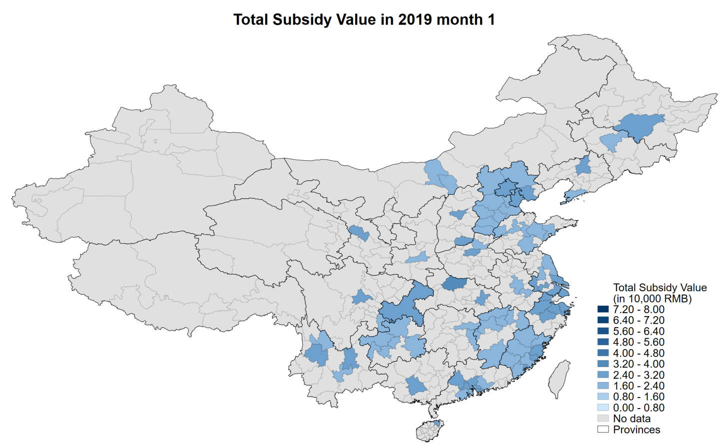

(a) Total Subsidy Amounts in January 2016




(b) Total Subsidy Amounts in January 2017




(c) Total Subsidy Amounts in January 2018




(d) Total Subsidy Amounts in January 2019

Figure 5: Maps of Total Subsidy in Sample Cities
Note: Subsidy Amounts presented by the maps indicate the average subsidy per vehicle.

restricted local governments from providing local subsidies that were more than 50% of the national subsidy.

Four maps showing the total subsidy amounts in January in sample cities from 2016 to 2019 are presented in Figure 5. The different colors depicted in the maps capture the spatial and temporal variations of the subsidy amounts.

The subsidy amounts used in this paper are the average amounts of the subsidy across all categories of EVs.[37] For instance, if 10,000 RMB, 20,000 RMB, and 30,000 RMB are the three subsidy categories, the subsidy amount used in this analysis would be the average of these three, 20,000 RMB. It would be ideal to use the actual average subsidy in each city calculated based on the shares of each category of EVs registered in the given cities; however, it is not feasible to do that, since detailed information about the vehicles such as their brand or driving range is not available for this dataset, thereby the subsidy for each specific EV is not known.

In addition to subsidies, some local governments also provide extra incentives to promote EV adoption. These include subsidies for using electricity at the public charging facilities or subsidies for installing private charging facilities, subsidies for EV taxis, and free parking in state-owned parking lots. Those additional benefits vary across cities, with details listed in Table 17 in Appendix A.3.

## 4.2 Passenger Vehicle Registration Data

Passenger vehicle registration data are used to construct the dependent variables, the log of EV shares and the log of EV registration per capita. EV shares indicate market penetration, or the market shares of EVs, which is the ratio of new EVs to all new passenger vehicles. It is obtained from monthly, city-level data (2016-2019) from the China Insurance Regulatory Commission.[38]

The term vehicle refers to a passenger vehicle, which means a vehicle with no more than 9 seats, and includes private use vehicles, taxis, and government use vehicles. One of the limitations of this data is that the use of the vehicles cannot be observed, making it impossible to separate private buyers from taxi owners or government procurements. However, according to the *Report on the Development of China Energy-saving and New Energy Vehicle (2017) and (2019)* by the *Evergrande Research Institution*, in 2016, nearly a half of all EVs were purchased by private buyers, with private buyers accounting for over half of the

[37] Regressions which use maximum subsidy amounts yield similar results.

[38] The data were obtained from www.dataisvision.com

EV registrations in 2017 and 2018. Data on the registration of new vehicles are based on compulsory traffic accident liability insurance data. Each observation includes time (year and month), vehicle type (gasoline, diesel, BEV, PHEV etc.), manufacturer type (domestic, joint venture, imported),[39] city, and quantity.

## 4.3 Demographic Data and Other Control Variables

Below is a brief description of the demographic data and other control variables used in this analysis.

| **Demographic Data** | **Level** | **Frequency** | **Source** |
|---|---|---|---|
| GDP per capita (in 1,000 RMB) | city-level | annual | Local Municipal Bureau of Statistics |
| Population (1,000) | city-level | annual | Local Municipal Bureau of Statistics |
| Urban land area ($km^2$) | city-level | annual | Local Municipal Bureau of Statistics |
| Government expenditure (in 1 million RMB) | city-level<br>province-level | annual | Local Municipal Bureau of Statistics |
| Government expenditure<br>on environmental protection (in 1 million RMB) | province-level | annual | Local Municipal Bureau of Statistics |
| Government expenditure<br>on education (in 1 million RMB) | city-level | annual | Local Municipal Bureau of Statistics |
| Gas price (RMB/ton) | province-level | monthly | National Development and<br>Reform Commission |
| Electricity price (RMB/kWh)[a] | province-level | monthly | |
| Number of charging facilities<br>(private/public, AC/DC) | province-level | monthly | China Electric Vehicle Charging<br>Infrastructure Promotion Alliance<br>(EVCIPA) Monthly Report |
| City tier (*1,2,3,4*) | city-level | 2017 | *City Beyond Data*<br>2017 Report[b] |

Notes: The Local Municipal Bureau of Statistics and National Development and Reform Commission Data are accessed from the CEIC Data: https://www.ceicdata.com/.

[a] Electricity price is the usage price for industry (35 kV & above).

[b] *City Beyond Data*: a sample report can be found at https://www.yicai.com/news/100200192.html.

Table 2: Description of Demographic Data and Other Control Variables

## 4.4 Summary Statistics

Table 3 below presents the summary statistics of the dependent and independent variables used in the paper. Summary statistics by year are displayed in Appendix A.1.

[39] Imported EVs are excluded from the analysis since they did not qualify for the subsidy.

| | mean | sd | min | median | max |
|---|---|---|---|---|---|
| EV share | 0.02 | 0.04 | 0.00 | 0.01 | 0.45 |
| Num/pop (number/thousand people) | 0.06 | 0.14 | 0.00 | 0.01 | 2.36 |
| Subsidy (in 10,000 RMB) | 3.85 | 2.18 | 0.00 | 3.88 | 7.98 |
| Local subsidy ratio | 0.34 | 0.36 | 0.00 | 0.30 | 1.06 |
| GDP per capita (in 1,000 RMB) | 82.13 | 37.37 | 24.12 | 77.32 | 203.49 |
| Pop density (1,000 people/$km^2$) | 0.78 | 0.90 | 0.06 | 0.59 | 6.73 |
| Charging points (1000) | 11.32 | 12.16 | 0.02 | 6.93 | 58.02 |
| Electricity price (RMB/kWh) | 0.74 | 0.09 | 0.40 | 0.76 | 0.91 |
| Gas/electricity price | 8.37 | 1.53 | 5.47 | 8.18 | 15.89 |
| Gas price (RMB/ton) | 6.07 | 0.54 | 4.95 | 6.13 | 7.42 |
| Govt. edu expenditure ratio | 0.18 | 0.03 | 0.10 | 0.18 | 0.27 |
| Govt. env expenditure ratio | 0.03 | 0.01 | 0.01 | 0.03 | 0.07 |
| Driving Restriction (0 or 1) | 0.19 | 0.39 | 0.00 | 0.00 | 1.00 |
| License restriction (0 or 1) | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 |
| License lottery winning rate (lag) | 0.93 | 0.26 | 0.00 | 1.00 | 1.00 |
| License auction price (in 1,000 RMB) | 2.84 | 12.66 | 0.00 | 0.00 | 95.10 |
| Extra subsidy dummy for charging/electricity (0 or 1) | 0.03 | 0.18 | 0.00 | 0.00 | 1.00 |
| EV Taxi subsidy dummy (0 or 1) | 0.07 | 0.26 | 0.00 | 0.00 | 1.00 |
| Free parking dummy (0 or 1) | 0.02 | 0.14 | 0.00 | 0.00 | 1.00 |
| Observations | 3945 | | | | |

Table 3: Summary Statistics

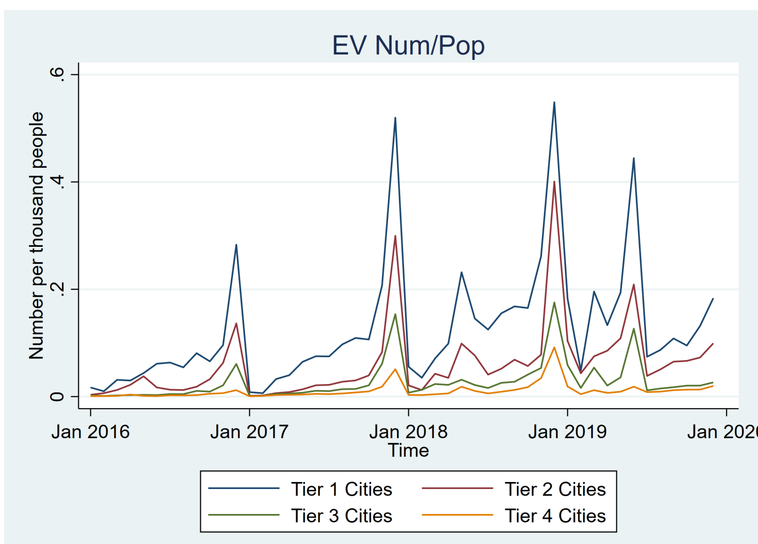



Figure 6: Newly Registered EVs per Capita for Cities in Different City Tiers

Figure 6 and Figure 7 present the mean of EVs' $Num/Pop$ and $EV\ share$ in different city tiers across time. $Num/Pop$ represents the newly registered number of EVs per capita, calculated by dividing EVs by the population. $EV\ share$ is the penetration or market share

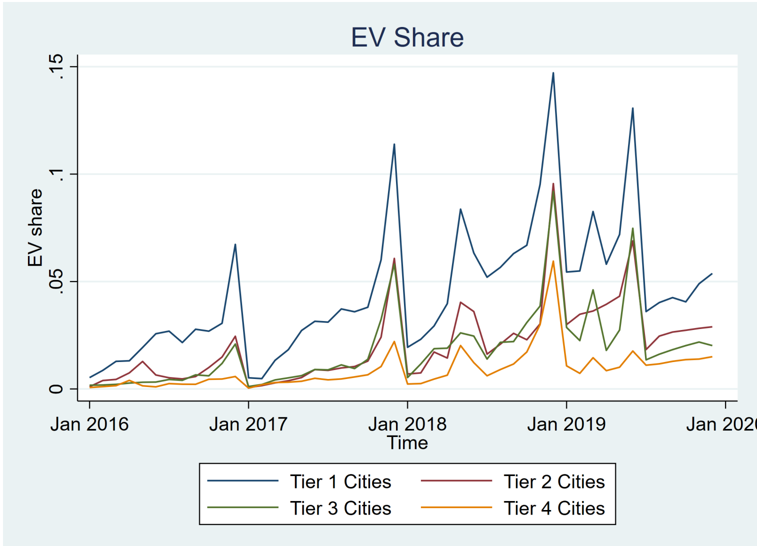



Figure 7: Newly Registered EV Shares for Cities in Different City Tiers

of the EVs, calculated by dividing the number of newly registered EVs by the total number of newly registered passenger vehicles.

# 5 Specification and Identification

This section presents details of the main specification and a discussion of identification and robustness checks. The main specification used in the study is a panel regression analysis with fixed effects. Additionally, a difference-in-differences analysis is conducted to provide causal evidence for the relationship between subsidies and EV adoption.

## 5.1 Main Specification

A Hausmann test was conducted to determine whether a fixed-effects model or a random-effects model was the preferred model to use with the data. The test revealed that a fixed-effects model was preferable.[40] The baseline specification is:

$$ln(EV_{it}) = \beta \cdot Sub_{it} + \theta \cdot DR_{it} + \gamma \cdot LicR_{it} + Controls'_{it} \cdot \delta + \alpha_i + \lambda_t + \epsilon_{it} \tag{1}$$

[40] In the Hausmann test, $H_0$ is that a random-effects model is preferred. The result shows that Prob$>\chi^2$ $=0$, which means $H_0$ is rejected, thus a fixed-effects model is preferred.

where $i$ indicates the city, $t$ indicates the time (month-year), and $EV_{it}$ is the EV share[41] or EVs per capita ($Num/Pop$) in city $i$ at time $t$. A log transformation is conducted, and the natural log of EV share (or EV per capita) is used as the dependent variable to get the errors closer to a normal distribution. $Sub_{it}$ is the total amount of subsidy, i.e., the sum of national and local subsidy amounts in city $i$ at time $t$. It is worth noting that $Sub_{it}$ essentially just captures the effects of local subsidies since national subsidies are the same across cities within the same year. Thus, variation over time of the national subsidy would be absorbed by the time fixed effects.[42] $DR_{it}$ is a dummy variable indicating the existence of driving restrictions in city $i$ at time $t$. $LicR_{it}$ is a dummy variable that equals 1 if a license plate registration quota exists in city $i$ at time $t$, and 0 otherwise. To further investigate the effects of license plate quotas using more detailed data, the dummy variable $LicR_{it}$ is replaced by two separate variables, lagged $License\,Lottery_{it}$ and lagged $License\,Auction_{it}$.[43] $License\,Lottery_{it}$ reflects how hard it is to get an ICEV license plate in the lottery, which is calculated as 1 - *average probability of winning a lottery.*[44] $License\,Auction_{it}$ represents the average auction price (in 1,000 RMB) for city $i$ at time $t$. Thus, a higher value of $License\,Lottery_{it}$ or $License\,Auction_{it}$ indicates that it is harder for an ICEV buyer to get a license plate due to a lower probability of winning the lottery or a higher price in the auction. $Controls'_{it}$ are control variables such as GDP per capita, population density, share of government expenditure on education, share of government expenditure on environmental protection, number of charging facilities, and the ratio of gas price to electricity price. $\alpha_i$ represents city fixed effects, while $\lambda_t$ represents time fixed effects. Month-year fixed effects are used, unless otherwise stated.

The baseline specification controls for socio-demographic variation across the entire sample and uses fixed effects to account for variation across individual cities and different time periods. However, subsidies may have heterogeneous effects in different groups of cities. Furthermore, the magnitude of the effects could depend on some of the socio-demographic

[41]EV share is calculated by dividing the number of monthly EV registrations by the registrations of all types of passenger vehicles. The results for BEV as the dependent variable are also shown.

[42]If national and local subsidies are included as separate variables, the national subsidy variable will be omitted.

[43]I also use the average of the previous four months instead of a one-month lag for $License\,Lottery_{it}$ and $License\,Auction_{it}$; these regressions yield similar results.

[44]The average probabilities of winning for cities without a license plate lottery policy are ones, so $License\,Lottery_{it} = 1 - 1 = 0$.

characteristics. Therefore, interaction terms are introduced in the specification shown below:

$$ln(EV_{it}) = \beta \cdot Sub_{it} + \theta \cdot DR_{it} + \gamma \cdot LicR_{it} + Controls'_{it} \cdot \delta + \sum_{j=2}^{4} \psi_j \cdot Sub_{it} \times Tier_{ij} + \phi \cdot Sub_{it} \times X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \quad (2)$$

where $Tier_{ij}$ categorizes cities based on the score ranking of cities in China from the *Cities Beyond Data* 2017 report by Yicai (see details in Appendix A.2); this categorization is frequently mentioned in the news and social media and therefore quite well-known in China. $Tier_{ij}$ is a dummy variable that equals 1 if city $i$ belongs to the $j$th tier ($j \in \{2, 3, 4\}$), as the comparison group is the first tier cities. Thus, the coefficient of $Sub_{it}$, $\beta$, is the effect of subsidies for the first-tier cities. $X_{it}$ includes three of the control variables used above: GDP per capita, share of government expenditure on education, and share of government expenditure on environmental protection. The reason for including the interactions of $Sub_{it}$ with these three control variables is because these variables could potentially influence subsidy effects. As shown in Jenn et al. (2018) and Ye et al. (2021), having knowledge of EVs and the associated incentives, as well as pro-EV attitudes could lead to different EV adoption in places with similar incentives. Consumers' awareness of EVs and EV-related policies could be affected by their economic conditions, education levels, and attitudes to environmental protection, which are reflected or partly reflected by the above-mentioned variables.

Additionally, three other incentives provided to EV buyers are included in the fixed effects regressions. The incentives are an extra subsidy for charging facility installation and electricity fees, a subsidy for taxis but not private use EVs, and limited-time free parking benefits. Accordingly, the specification is further extended to the following:

$$ln(EV_{it}) = \beta \cdot Sub_{it} + Extra'_{it} \cdot \mu + \theta \cdot DR_{it} + \gamma \cdot LicR_{it} + Controls'_{it} \cdot \delta + \sum_{j=2}^{4} \psi_j \cdot Sub_{it} \times Tier_{ij} + \phi \cdot Sub_{it} \times X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \quad (3)$$

where $Extra'_{it}$ is a vector including the three dummies, $i.ExtraSub_{it}$, $i.TaxiSub_{it}$, and $i.Parking_{it}$, which indicate whether city $i$ at time $t$ has the extra incentives mentioned above.

One may worry that gasoline and electricity prices are "bad controls" since they could possibly be affected by subsidies. For instance, in a free market, gasoline prices may decrease, and electricity prices may increase if subsidies for EVs increase, since more car buyers would switch from conventional gasoline cars to EVs. However, this situation is highly unlikely to apply to China, given that the gasoline and electricity markets in China are highly regulated and the prices are mostly set by governments.[45] The gasoline price reflects the price in the global markets and the electricity price reflects the costs of generating electricity and the types of electricity usage; therefore, in China, these two prices should be exogenous to the EV demand and the subsidies for EVs.

Another concern related to the bad control problem is that the number of charging facilities might also be influenced by subsidies. This is a valid concern because offering higher subsidies probably leads to lower investments towards the installation of charging facilities, given that governments have limited budgets. To alleviate this problem, the lagged number of charging facilities is used in an additional analysis, presented in Appendix A.6. The regressions with lagged number of charging facilities yield similar results to the ones with the current number of charging facilities.

Lastly, one may also worry that license plate registration quotas and driving restrictions are correlated with subsidy values. Cities with either or both of the restrictions may be inclined to offer lower subsidies. The reason it should not be a concern in this analysis is that the coefficients for both the two restrictions are not statistically significant when running the regression of subsidy on all of the other independent variables.

I do not include the price of an average EV or the total ownership cost of an EV in the analysis, because the prices or ownership costs are highly similar across different cities in China. Furthermore, any temporal variations in costs (most likely decreasing costs over time) would be captured by the time fixed effects.

## 5.2 Identification Strategy

There are several threats to identification of estimating the subsidy effects. The first threat is that subsidies are not randomly assigned. For instance, a possible concern is that a higher GDP per capita might result in a higher subsidy. However, results from a VIF test show that all control variables, including GDP per capita, have VIF values below 5. Furthermore,

[45] The baseline prices of gasoline and electricity are determined by National Development and Reform Commission (NDRC). The baseline retail fuel price is adjusted based on the changes in the global crude oil benchmark prices, see: https://www.reuters.com/world/china/chinas-retail-diesel-gasoline-prices-hit-record-highs-2022-03-31. The industrial electricity rates vary across regions but are still determined by the national and local governments as well as the state-owned power companies, see: https://www.china-briefing.com/news/chinas-industrial-power-rates-category-electricity-usage-region-classification/ and https://chinadialogue.net/zh/4/44327/ (in Chinese).

a scatter plot of GDP per capita and subsidy for each year displays no correlation between these variables. These findings suggest that correlations between independent variables are not a concern in this study.[46] In addition, the magnitude of subsidies could potentially be correlated with city characteristics,[47] such as local governments' budgets for additional subsidies or how high the promotion of environmentally friendly cars ranks on the list of local governments' priorities. To address this issue, the baseline specification in equation (1) is adjusted to the one in equation (2). First, both socio-demographic variables and their interactions with subsidy values are included in the main specification. Furthermore, I also include interaction terms between the subsidy and the city tiers to distinguish between subsidy effects for different city tiers. Additionally, I utilize the difference-in-differences method to exploit the sudden change in national policy that affected some of the sampled cities, which is demonstrated in detail in the following subsection. The DID analysis also offers support for the causal relationship between subsidies and EV adoption.

The second identification threat is omitted variable bias. City fixed effects help to absorb the unobserved city characteristics that are invariant over time but could potentially influence the local subsidy policy. For instance, a city government might choose to offer a smaller amount of local subsidy if potential buyers have pro-technology attitudes. Time fixed effects capture the demand shock or unobserved policies at the national level that could potentially confound the subsidy policies. Another possible factor missing from the main specification is consumers' knowledge of EVs. Since having more knowledge of EVs could increase people's acceptance of buying and driving EVs, governments might be inclined to offer fewer financial incentives if potential car buyers have more knowledge of EVs. To alleviate this problem and capture the positive externalities of the EV adoption, I include one or two lags of the dependent variable in the robustness checks; this is because more EV shares in a previous period of times would indicate a higher probability of seeing them on the road or knowing someone who owns an EV, thus increasing knowledge about EVs and the likelihood of purchasing one.

The third threat to identification is the possible reverse causality between EV market shares and the number of charging facilities. The increasing number of charging facilities can increase EV adoption, but a higher EV adoption rate can also lead to more investments in

[46] There is a relatively low correlation between subsidies and GDP per capita (correlation coefficient of 0.05). Nevertheless, I attempt to address the issue by running regressions that exclude GDP per capita. The analyses yield similar results.

[47] Another potential concern is the simultaneity bias, meaning that cities with higher demand for EVs could be inclined to provide more subsidies. However, it should not be an issue in this analysis, since the correlation between EV market shares and subsidies is negative and relatively low (correlation coefficient of -0.0804).

charging facilities. To mitigate the issue, I replace the number of charging facilities with the lagged number of charging facilities, which is directly correlated with the current number of charging facilities. Intuitively, lagged number of charging facilities could affect EV adoption in the current period, and not vice versa. The results are similar to the ones using current number of charging facilities.

Several other potential biases and caveats should be noted. First, there are some data limitations; though the EV registration data are at the city level and are recorded monthly, the data for the control variables are mainly recorded annually, with some controls being measured at the province level instead of the city level. Therefore, potential differences across cities within the same province cannot be captured. For instance, the number of charging facilities is the total number of charging facilities in one province, yet variations likely exist across cities within the same province. Additionally, some control variables are not the perfect proxies for the demographic characteristics I would like to control for. For example, the share of government expenditure allocated to education cannot perfectly reflect the educational levels of city residents.

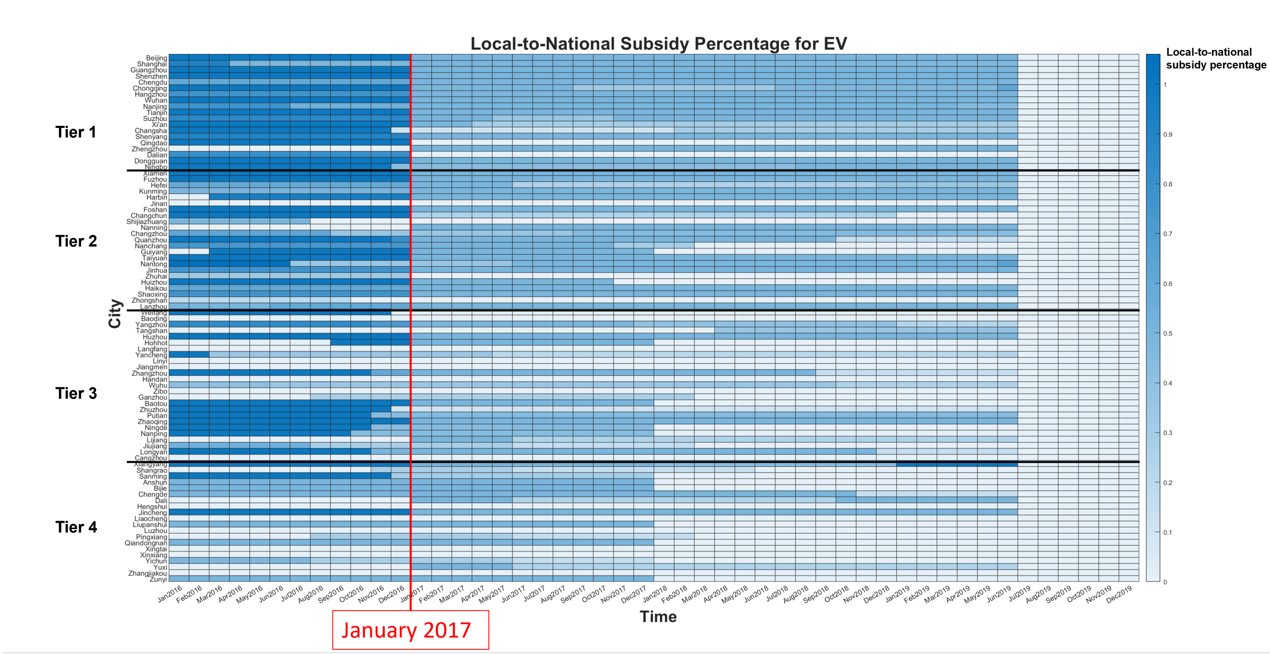
Second, two kinds of measurement errors exist for the variable $Sub_{it}$. One error is that $Sub_{it}$ may not accurately reflect the actual average subsidy. The actual subsidy should be calculated based on the percentage of EVs belonging to the different subsidy categories (as shown in Figure 3, EVs with different driving ranges received different subsidies); however, the data only show the total number of city-level EV registrations. The other error is related to the timeliness of the subsidy. To record when the subsidy was first introduced in each city, I use the starting date stated in local policy documents.[48] However, a few cities or regions announced or detailed their subsidy policies long after their stated implementation dates, such as announcing details of a subsidy introduced in 2016 only in 2018. In this case, cities are assumed to have no local subsidies in 2016, the specified time of subsidy in the policy. However, it is also possible that the manufacturers or the dealers were aware of this information before the documents were released.[49] To mitigate this problem, in the robustness checks, I use a dummy variable to indicate the presence of local subsidies rather than using the subsidy values, while also running regressions on quarterly EV registrations.

[48] If the documents were not available or can no longer be viewed, related news was cross-checked to determine the starting time of the subsidies.

[49] As subsidy is given to the dealers, who are then asked to sell the EV to the buyer at a lower price, after deducting the subsidy from the initial price.

### 5.2.1 Difference-in-Differences Method

Starting in 2017, the central government banned local governments from providing local subsidies that were more than a 50% of the national subsidy, i.e., the local-to-national subsidy percentage[50] could not exceed 50%. The policy was announced by the central government at the end of 2016. As a result, Figure 8 reveals a sharp change in the local-to-national subsidy percentage at the start of 2017 for nearly half of the sampled cities.




Note: For some cities, the local-to-national subsidy percentages can be directly found or calculated for each category in the policy documents. However, a few cities provided their own subsidy schemes that do not differentiate EVs by their driving ranges; the average amounts are used in these cases.

Figure 8: Local-to-National Subsidy Percentage for EVs

The treatment group includes cities with a local-to-national subsidy percentage higher than 50% before January 2017. The remaining cities were allocated to the control group. The average total subsidies in each group are graphically presented in Figure 11 in Appendix A.11. There are 38 cities in the treatment group and 49 cities in the control group.

By exploiting this sudden and substantial drop in subsidies for only some of the sampled cities, the difference-in-differences method can be applied to investigate the effects of the reduction in subsidies. Cities with local subsidies lower than or equal to 50% of the national subsidy (local-to-national subsidy percentage $\leq 50\%$) before 2017 were not affected since they already satisfied the newly imposed requirement. Therefore, those cities have had to make

[50] Local-to-national subsidy percentage is the percentage of local subsidy in relation to the national subsidy.

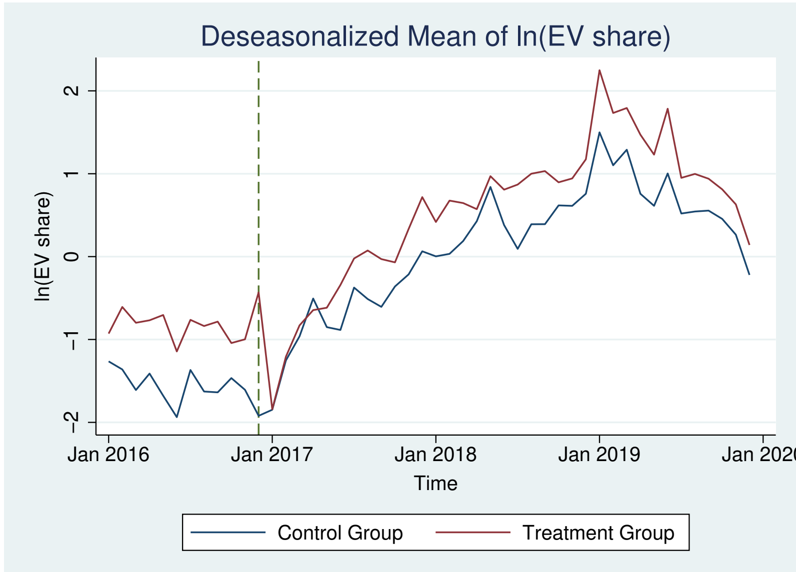



Figure 9: Deseasonalized Mean of $ln(EV\ share)$ for Treatment Group and Control Group

relatively much smaller adjustments in terms of the local-to-national subsidy percentage.[51] However, cities with local subsidies higher than 50% of the national subsidy (local-to-national subsidy percentage $>$ 50%) before 2017 were affected, as these local governments had to adjust their subsidies.[52] Therefore, the unaffected cities can be considered to be the non-treatment or control group, while the affected cities are the treatment group. The basic DID model is:

$$ln(EV_{it}) = \beta_0 + \beta_1 \cdot Treat_i + \beta_2 \cdot Post17_t + \beta_3 \cdot Post17_t \times Treat_i + \epsilon_{it} \quad (4)$$

where $Treat_i$ is a dummy variable indicating whether the city $i$ is in the treatment group, i.e., was affected by the policy. Alternatively, $Treat_i$ can be a continuous variable reflecting treatment intensity, which is measured by the difference between the local-to-national subsidy percentage before the new policy and the 50% limit affecting the treatment group. For example, if a city offered a local subsidy equivalent to 60% of the national one (local-to-national subsidy percentage = 60%) in December 2016, the treatment intensity would be calculated as $0.6 - 0.5 = 0.1$. For cities in the control group, the intensity value would be zero. $Post17_t$ is a dummy variable that equals 1 if the time $t$ is after 2017. The coefficient

[51]Total and local subsidy amounts still decreased, but this was expected by the buyers, given that the national subsidy also kept decreasing based on the national plan.

[52]If relevant policy documents stating the exact amount or local-to-national subsidy percentage cannot be found, it is reasonable to assume that buyers would expect to receive a local subsidy of at most 50% of the national subsidy.

of interest, $\beta_3$, reflects the average treatment effect.

When including the other control variables and the interaction terms, the specification of the DID model becomes the following:[53]

$$ln(EV_{it}) = \beta \cdot Post17_t \times Treat_i + \theta \cdot DR_{it} + \gamma \cdot LicR_{it} + Controls'_{it} \cdot \delta + \sum_{j=2}^{4} \psi_j \cdot Post17_t \times Treat_i \times Tier_{ij} + \alpha_i + \lambda_t + \epsilon_{it} \quad (5)$$

It is worth mentioning that, although the difference between the numbers of treated and control cities is small, the numbers are not distributed evenly across the different tiers. In other words, it is possible that cities were not randomly assigned to the treatment condition. That is, those cities which chose to provide local subsidies that were over 50% of national subsidy may have done so due to factors related to their specific budgets, or economic and environmental conditions. As seen from Figure 8, cities with higher rankings in the tier system tended to provide higher local subsidies, thus having a higher probability of being in the treatment group. As a result, 15 out of 19 first-tier cities, 15 out of 23 second-tier cities, but only 7 out of 28 third-tier cities, and 1 out of 17 fourth-tier cities are placed in the treatment group (the number of cities in each tier is presented in Table 4). As choosing to offer a higher local subsidy is not a random selection, the data may not be ideal for a difference-in-differences analysis.

| Tier | Control Group | Treatment Group |
|---|---|---|
| 1 | 4 | 15 |
| 2 | 8 | 15 |
| 3 | 21 | 7 |
| 4 | 16 | 1 |
| Total | 49 | 38 |

Table 4: Counts of Cities in Different Tiers

However, the timing of the treatment implementation is unexpected, given that the announcement was made only two days before the first day of 2017.[54] Additionally, due to the already established subsidy plan of the national government, people would expect the magnitude of the national subsidy to keep decreasing, but expect the local-to-national subsidy

[53] $Post17_t$ and $Treat_i$ are not included because $Post17_t$ will be captured by the time fixed effects, $\lambda_t$, and $Treat_i$ will be captured by city fixed effects, $\alpha_i$.

[54] Many cities only started to offer local subsidies in 2016 and nearly half of the cities in the sample were providing local subsidies of more than 50% of the national subsidy.

percentage to remain the same, meaning that there would be an equivalent decrease in local subsidies. The policy introducing the additional restriction would further reduce the local subsidy for some cities.

Another point worth noting, one that validates the DID analysis, is that the parallel pre-trend assumption is satisfied. Figure 9 shows the deseasonalized mean of the dependent variable, $ln(EV\,share)$, before and after January 2017. The trends in the pre-treatment period are nearly parallel, which satisfies the parallel pre-trend assumption necessary for applying the DID method. In addition, the lag and lead coefficients with 95% confidence intervals for a panel event study are plotted in Figure 15 in Appendix A.11.3. The plots and the F-statistics of joint significance tests for lags also show that the parallel pre-trend assumption is satisfied.

## 5.3 Robustness Checks

Several robustness checks are conducted to address the concerns mentioned above and to assess the validity and stability of the main results. These robustness checks provide further support for the main results.

First, although PHEVs and BEVs are both categorized as EVs, they use quite different technologies and might be considered to be different types of vehicles by car buyers. Since BEVs were the main focus of governments' promotion plan of EVs in China and accounted for a larger share of EVs compared to PHEVs, an additional analysis is conducted which only examines the effects of subsidies on BEVs. I remove the PHEVs and only use BEVs to construct the dependent variable, the log of BEV share. $Sub_{it}$ is also re-calculated, now representing the average total subsidy value for only BEVs.

Second, to mitigate potential measurement errors, I replace the amounts of the subsidies with a dummy variable indicating the existence or absence of local subsidies. The same specifications are applied, and regressions are rerun. Additionally, I also aggregate the monthly data into quarterly data and rerun the regressions. Third, lagged dependent variables are added into the regressions to capture the positive externalities of existing EVs. The resulting specification is:

$$\begin{aligned} ln(EV_{it}) = \sum_{k}^{1,2} \pi_k \cdot ln(EV_{i,t-k}) + \beta \cdot Sub_{it} + Extra'_{it} \cdot \mu + \theta \cdot DR_{it} + \gamma \cdot LicR_{it} \\ + Controls'_{it} \cdot \delta + \sum_{j=2}^{4} \psi_j \cdot Sub_{it} \times Tier_{ij} + \phi \cdot Sub_{it} \times X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \end{aligned} \quad (6)$$

One potential concern is that including lagged dependent variable terms violates strict exogeneity. However, the number of time periods, $T$, is relatively large in this study ($T = 48$), so that the dynamic bias becomes insignificant, indicating that a fixed effects model should be adequate (Roodman, 2009).

# 6 Main Results

## 6.1 Baseline Regression and Heterogeneous Effects

A residual versus fitted value plot, as well as a likelihood-ratio test, were conducted to assess whether homoskedasticity is satisfied in the regression analysis. Both results reveal heteroskedasticity in the data. Therefore, the regressions presented in this paper use cluster-robust variance-covariance estimator by city to allow for intra-city correlation, unless otherwise stated.

Table 5 reports the baseline results and the results of the regressions with interactions for $ln(EV\, share)$ as the dependent variable. The corresponding results when using $ln(Num/Pop)$ as the dependent variable are similar, as displayed in Appendix A.4 Table 18. All regressions include city fixed effects and month-year fixed effects. Column (1) shows the baseline result without including the interaction terms, i.e., specification (1). Columns (2) through (6) show the results for specification (2) with the interaction terms. The variable *Subsidy* has a positive and generally significant coefficient, except for the results in column (2), when only the interaction term of *Subsidy* and *GDP per capita* is added.

Columns (5) and (6) are preferred since column (5) shows the average subsidy effects in different tiers, while (6) is the one with all of the possible interaction terms. In column (5), where the interaction term between $Tier$ and *Subsidy* is included, we can see that the subsidy effect is heterogeneous across cities in different tiers. On average, first-tier cities have the largest subsidy effects; with every 10,000 RMB increase in subsidies resulting in a 17.2% increase in the log of EV market share, i.e., a 18.77% ($e^{0.172} - 1 = 0.1877$) increase in EV market share. By contrast, second-, third- and fourth-tier cities have much smaller subsidy effects on average, with an increase of only about 5%, 6.2% and 0.7%, respectively.

In column (6), where all interactions are included, the results show that, after differentiating between cities in different tiers, subsidy effects are smaller when the GDP per capita is higher and when the share of government expenditure allocated to education or environmental protection is larger. The summary statistics of *Subsidy*, *GDP per capita*, *Edu Exp R*, and *Env Exp R* by city tier are presented in Table 7. For a first-tier city with medium $GDP\,per\,capita$ (123.8152 thousand RMB), $Edu\,Exp\,R$ (0.1445), and $Env\,Exp\,R$ (0.0275), the log change of EV market share resulting from a unit (10,000 RMB) increase in $Subsidy$ is 0.1668,[55] which can be translated to an 18.15% increase in the EV market share. For a second-tier, third-tier, or fourth-tier city with medium $GDP\,per\,capita$, $Edu\,Exp\,R$, and $Env\,Exp\,R$, the log increase of the EV market share is 0.05543, 0.06872, and 0.04857, respectively; these increases are much smaller than the one for a medium first-tier city.

Having a negative coefficient for the interaction term means that the subsidy effects are lower when the interaction variable has a higher value. For example, when looking at the $Subsidy \times GDP\,per\,capita$ interaction in column (6), within the same city tier, a 1,000 RMB increase in GDP per capita leads to a one unit increase in $Subsidy$ having a smaller effect on EV adoption rates, which is a decrease of approximately 0.116 percentage points in subsidy effects. This means that for a first-tier city with $Edu\,Exp\,R = 0.15$ and $Env\,Exp\,R = 0.03$ (the medium value), an increase in its GDP per capita by one unit, from 100,000 to 101,000 RMB, the subsidy effect on EV adoption rates decreases from 19.18% to 19.04%.[56] Therefore, people in cities that are less economically developed, i.e., have a lower GDP per capita, tend to be more responsive to subsidies, holding city tier constant.

Additionally, within the same city tier, a lower share of government expenditure allocated to education or environmental protection yields a larger positive effect of the subsidies on EV adoption. According to regression (6), the increase of the EV market share as a result of the subsidy would be decreased by about 1.352 percentage points and 4.591 percentage points with every 1 percentage point increase in $Edu\,Exp\,R$ and $Env\,Exp\,R$, respectively. The reason for this could be that, when governments spend more on education, their better-educated residents could be more likely to understand the benefits of EV ownership or be more willing to accept this new technology, therefore being motivated to buy EVs even with smaller subsidies. In addition, higher environmental protection could make people feel less worried about potential pollution issues, which would make them less responsive to the available subsidies for EVs. One thing worth noting is that the share of government expenditure on environmental protection comes from province-level data and its magnitude is relatively small (0.06814 at its maximum value); therefore, this variable does not capture the difference across cities in the same province.

$GDP\,per\,capita$, $Pop\,Density$, $Charging\,Pts$, and $Gas/Electricity$ are not statistically significant across all regressions. The coefficients for $GDP\,per\,capita$ are quite small and

[55] $0.632 - (0.00116 * 123.8152) - (1.352 * 0.1445) - (4.591 * 0.0275) = 0.1668$

[56] $0.632 - (1.352 * 0.15) - (4.591 * 0.03) - (0.00116 * 100) = 0.17547$, and $e^{0.17547} - 1 = 0.1918$; $0.632 - (1.352 * 0.15) - (4.591 * 0.03) - (0.00116 * 101) = 0.17431$, and $e^{0.17431} - 1 = 0.1904$.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.106* | 0.0386 | 0.372*** | 0.244*** | 0.172*** | 0.632*** |
| | (0.064) | (0.084) | (0.098) | (0.078) | (0.061) | (0.143) |
| GDP per Capita | -0.00319 | -0.00431 | -0.00243 | -0.00151 | 0.000219 | 0.00371 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Pop Density | -1.249 | -0.879 | -0.589 | -0.861 | -0.914 | -0.667 |
| | (0.778) | (0.807) | (0.762) | (0.740) | (0.731) | (0.822) |
| Charging Pts | -0.00972 | -0.00568 | -0.0133 | -0.0110 | -0.00509 | -0.0170 |
| | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) |
| Gas/Electricity | -0.0958 | -0.0893 | -0.0756 | -0.0903 | -0.0969 | -0.0857 |
| | (0.062) | (0.061) | (0.060) | (0.063) | (0.061) | (0.061) |
| Edu Exp R | 1.208 | 1.879 | 7.812* | -0.209 | 1.768 | 4.906 |
| | (4.089) | (4.105) | (4.655) | (4.119) | (4.201) | (4.912) |
| Env Exp R | 6.979 | 6.796 | 6.698 | 22.55* | 7.590 | 21.58* |
| | (10.723) | (10.231) | (9.385) | (13.020) | (9.247) | (11.695) |
| License Restriction | 1.170*** | 1.167*** | 1.231*** | 1.209*** | 1.118*** | 1.209*** |
| | (0.123) | (0.122) | (0.119) | (0.128) | (0.148) | (0.154) |
| Driving Restriction | 0.269* | 0.270* | 0.318** | 0.218 | 0.350** | 0.331** |
| | (0.150) | (0.153) | (0.148) | (0.155) | (0.146) | (0.155) |
| Subsidy × GDP per Capita | | 0.000690 | | | | -0.00116* |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.569*** | | | -1.352** |
| | | | (0.466) | | | (0.553) |
| Subsidy × Env Exp R | | | | -5.082* | | -4.591* |
| | | | | (2.575) | | (2.314) |
| Tier=2 × Subsidy | | | | | -0.122*** | -0.108** |
| | | | | | (0.044) | (0.049) |
| Tier=3 × Subsidy | | | | | -0.110*** | -0.0944* |
| | | | | | (0.040) | (0.053) |
| Tier=4 × Subsidy | | | | | -0.165*** | -0.137* |
| | | | | | (0.056) | (0.076) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses

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

Note: The corresponding results when using $ln(Num/Pop)$ as the dependent variable are similar, as displayed in Appendix A.4 Table 18.

Table 5: Baseline and Heterogeneous Effects for $ln(EV\ share)$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.105 | 0.0486 | 0.369*** | 0.250*** | 0.171*** | 0.666*** |
| | (0.063) | (0.085) | (0.097) | (0.079) | (0.061) | (0.143) |
| GDP per Capita | -0.00297 | -0.00393 | -0.00222 | -0.00117 | 0.000228 | 0.00425 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Pop Density | -1.546* | -1.194 | -0.876 | -1.203 | -1.178 | -1.103 |
| | (0.820) | (0.856) | (0.807) | (0.779) | (0.790) | (0.859) |
| Charging Pts | -0.0103 | -0.00694 | -0.0139 | -0.0118 | -0.00588 | -0.0189* |
| | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) |
| Gas/Electricity | -0.0969 | -0.0916 | -0.0771 | -0.0908 | -0.0982 | -0.0867 |
| | (0.062) | (0.061) | (0.060) | (0.062) | (0.061) | (0.060) |
| Edu Exp R | 1.245 | 1.803 | 7.794* | -0.225 | 1.751 | 4.910 |
| | (4.092) | (4.105) | (4.641) | (4.124) | (4.201) | (4.891) |
| Env Exp R | 8.213 | 8.004 | 7.957 | 24.65** | 8.650 | 24.09** |
| | (10.354) | (9.996) | (9.123) | (12.336) | (9.093) | (11.296) |
| License Lottery (lag) | 1.483*** | 1.462*** | 1.544*** | 1.538*** | 1.378*** | 1.537*** |
| | (0.291) | (0.299) | (0.304) | (0.298) | (0.290) | (0.293) |
| License Auction (lag) | 0.0147** | 0.0128* | 0.0140** | 0.0180** | 0.0122* | 0.0195*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) |
| Driving Restriction | 0.239 | 0.243 | 0.289* | 0.182 | 0.320** | 0.291* |
| | (0.149) | (0.152) | (0.147) | (0.153) | (0.145) | (0.154) |
| Subsidy × GDP per Capita | | 0.000583 | | | | -0.00132** |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.557*** | | | -1.410** |
| | | | (0.463) | | | (0.553) |
| Subsidy × Env Exp R | | | | -5.327** | | -4.966** |
| | | | | (2.593) | | (2.350) |
| Tier=2 × Subsidy | | | | | -0.121*** | -0.108** |
| | | | | | (0.044) | (0.049) |
| Tier=3 × Subsidy | | | | | -0.105** | -0.0909* |
| | | | | | (0.040) | (0.053) |
| Tier=4 × Subsidy | | | | | -0.158*** | -0.132* |
| | | | | | (0.055) | (0.075) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses

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

Note: The corresponding results when using $ln(Num/Pop)$ as the dependent variable are similar, as displayed in Appendix A.4 Table 19.

Table 6: Baseline and Heterogeneous Effects, with *License Lottery* and *License Auction*

| | Tier | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | Total |
| Subsidy | | | | | |
| Minimum value | 0 | 0 | 0 | 0 | 0 |
| First quartile | 2.862054 | 2.65005 | 2.561715 | 1.7667 | 2.65005 |
| Second quartile | 4.65 | 4.65 | 3.5334 | 3.1667 | 3.875 |
| Third quartile | 4.75005 | 4.75005 | 4.65 | 3.875 | 4.75005 |
| Maximum value | 7.75 | 7.9825 | 7.75 | 7.75 | 7.9825 |
| Number of non-missing values | 910 | 1,083 | 1,258 | 694 | 3,945 |
| GDP Per Capita | | | | | |
| Minimum value | 58.283 | 52.723 | 24.116 | 24.54412 | 24.116 |
| First quartile | 97.47 | 72.465 | 48.562 | 32.219 | 53.932 |
| Second quartile | 123.8152 | 88.456 | 66.76 | 40.741 | 77.325 |
| Third quartile | 143.638 | 107.4948 | 83.44 | 49.806 | 105.7107 |
| Maximum value | 203.489 | 175.5 | 136.021 | 81.667 | 203.489 |
| Number of non-missing values | 910 | 1,083 | 1,258 | 694 | 3,945 |
| Edu Exp R | | | | | |
| Minimum value | .0984856 | .1084442 | .1194436 | .1368592 | .0984856 |
| First quartile | .1293046 | .1528046 | .1667191 | .1756007 | .1502984 |
| Second quartile | .1444857 | .1728498 | .1906713 | .1923392 | .1769004 |
| Third quartile | .1651052 | .1907046 | .2103767 | .2041205 | .2000134 |
| Maximum value | .2385273 | .2341693 | .2634004 | .2701593 | .2701593 |
| Number of non-missing values | 910 | 1,083 | 1,258 | 682 | 3,933 |
| Env Exp R | | | | | |
| Minimum value | .0176502 | .01496 | .0205421 | .0207707 | .01496 |
| First quartile | .0226748 | .0257567 | .0257567 | .0271855 | .0257567 |
| Second quartile | .0275025 | .0288103 | .0291115 | .0303035 | .0288103 |
| Third quartile | .0340346 | .0349633 | .0353582 | .0434414 | .0353582 |
| Maximum value | .06814 | .060476 | .060476 | .060476 | .06814 |
| Number of non-missing values | 910 | 1,083 | 1,258 | 694 | 3,945 |

Table 7: Summary Statistics by City Tier

cannot be differentiated from zero, implying that GDP per capita alone does not explain the change in the EV market share.

The coefficient for population density is negative but not statistically significant. Although Tanaka et al. (2011) indicated that shorter travel distances resulting from higher urban density might make EVs more attractive due to their limited driving range, consumer anxiety over driving range might have become increasingly alleviated as the driving range of EVs has been consistently increasing over time. Moreover, the public transportation systems of densely populated Chinese cities are likely to be well-developed and can thus cover most residents' intra-city travel needs, sometimes even facilitating inter-city travel. This means that residents of high-density cities would have fewer incentives to purchase EVs. Therefore, it is very likely that the coefficient of $Pop\,density$ reflects the net impact of shorter travel distances and a well-developed public transportation network, which explain the mixed results. This would be consistent with Sierzchula et al. (2014), who found that urban density is not an influential factor for EV adoption.

Similarly, the coefficient for $Charging\ Pts$ is negative but close to zero and non-significant, which means that the effect of increasing number of charging facilities is negligible.[57] One of the reasons for that could be that the number of existing charging facilities was too small to positively influence EV adoption among car buyers. Indeed, it is possible that in most Chinese cities within the sample, the threshold number of charging facilities needed to promote EV adoption has not yet been reached. Furthermore, due to data limitations, the number of charging facilities included in this analysis represents the cumulative number for each province, which means that it cannot reflect the differences in the total number of charging facilities across cities within the same province. This number does also not provide any information on the density or the accessibility of the charging facilities within a city. Thus, it is possible that reducing some of the infrequently used charging facilities and setting up additional charging facilities at busier locations could result in fewer total charging facilities but still lead to greater EV adoption by increasing convenience and accessibility.

The coefficient for $Gas/Electricity$ is also negative. This result initially appears to be counterintuitive, because higher relative fuel prices for ICEVs to EVs indicate relatively lower operating expenses of EVs, which could motivate car buyers to switch from ICEVs to EVs. However, the effect of gasoline prices has been found to be inconsistent in existing studies. For instance, Sierzchula et al. (2014) also found a negative and non-significant effect of fuel prices. This could be because buyers do not usually have a clear idea of the operating

[57]This effect was checked for both public and private charging facilities, yielding similar results. The results for $ln(EV\ share)$ using lagged number of charging facilities are presented in Appendix A.6 Table 21.

expenses of EVs and cannot make an accurate assessment of how much money they would save in the long term relative to owning an ICEV. Instead, buyers may focus primarily on the purchase price (Levine et al., 1995). This assumption is supported by surveys conducted by Caperello and Kurani (2012) and Turrentine and Kurani (2007), who each showed that potential adopters of fuel-saving vehicles lack the knowledge necessary for calculating the actual expenses of driving an ICEV. Furthermore, the extra fee charged by public charging facilities on top of the electricity fee makes it harder for potential EV buyers to accurately compare the operating expenses of conventional ICEVs and EVs.[58]

Two factors, *License Restriction* and *Driving Restriction*, have positive and statistically significant coefficients across all regressions except in column (4) for *Driving Restriction*. With everything else constant, having license plate registration quotas in place increases the EV market share by 222.20% ($e^{1.170} - 1 = 2.2220$), while having driving restrictions in place increases the EV market share by 30.87% ($e^{0.269} - 1 = 0.3087$) when we look at the baseline results. The results are consistent with the findings of other studies that focused on the Chinese EV market and included one or both of the two restrictions (Ma et al., 2017; Wang et al., 2017; Qian et al., 2019; Chi et al., 2021; Li et al., 2022). By 2019, 8 out of the 87 cities in this study had implemented license plate registration quotas and 26 out of the 87 cities had implemented driving restrictions (details on the policies are presented in Sections 3.3 and 3.4). Those two restrictions only apply to ICEVs except in Beijing.[59] This implies that people who consider purchasing a vehicle in cities with license plate registration quotas would be more motivated to switch from ICEVs to EVs to save time or money. These results suggest that restrictions on ICEVs are much more effective at promoting EV adoption than directly giving consumers an additional 10,000 RMB in subsidies. Driving restrictions also help promote the EV market share, with a smaller coefficient than that of license plate registration quota. The smaller effect is easily explained by the fact that driving restrictions only partially restrict the use of ICEVs, which means that those buyers who do not need to use their vehicles during the restricted times or in the restricted areas would remain unaffected.

To further explore the relationship between license plate quota policies and EV adoption, the *License Restriction* variable is replaced by two variables, the lags of $License\ Lottery_{it}$

[58] News about unexpected service fees for public charging facilities: `https://www.sohu.com/a/123799384_294030`. In China, most residents in urban areas only have access to public charging facilities.

[59] EV buyers in Beijing also need to enter lotteries in order to get license plates. PHEV buyers are in the same lottery pool as the ICEV buyers, while BEV buyers are in another pool, which has a higher probability of being drawn.

and $License\,Auction_{it}$.[60] $License\,Lottery_{it}$ is calculated as 1 - *average probability of winning a lottery*, and $License\,Auction_{it}$ is the average auction price (in 1,000 RMB) of an ICEV license plate. The corresponding results of Table 5 are shown in Table 6. Using the coefficients in column (5), we can conclude that, a 1 percentage point decrease in the probability of winning a lottery is associated with a 1.378% increase in EV market share. Additionally, a 1,000 RMB increase in the auction price of an ICEV license plate is correlated with a 1.22% increase in EV market share. Despite a slight change in the significance level for $Driving\,Restriction$ in the first two columns, the results for other variables are similar to the ones in Table 5, especially for the preferred specifications, columns (5) and (6).

### 6.2 Regressions with Extra Incentives

In addition to subsidies, some local governments also provide extra incentives to promote EV adoption. These include subsidies for using electricity at the public charging facilities or subsidies for installing private charging facilities, subsidies for EV taxis, and free parking in state-owned parking lots. Those additional benefits vary across cities, with details listed in Table 17 in Appendix A.3. $Extra\,Subsidy$ indicates the additional subsidies for charging facility installation or electricity fees, $Taxi\,Subsidy$ represents the local subsidy given to EV taxis, $Free\,Parking$ represents the cases in which policy documents specifically state that there are free parking or reduced fee benefits for EVs in public or state-owned parking lots.

As seen from the regression results in Table 8, only the extra subsidy for charging and electricity has positives and statistically significant effects, remaining significant across the various regression specifications. This suggests that, on average, providing additional subsidies for charging facilities and electricity leads to an increase of EV market share of 123.67%.[61] By contrast, subsidies designated to taxis and provision of free parking do not significantly impact EV adoption in any of these specifications. However, we should interpret the results for the regressions including the extra subsidy with caution, as only a small share of the sampled cities (4 out of 87) provide this extra subsidy for EV taxis, and it is possible that other unobserved factors have not been captured by the data.

Additionally, the results for the *Subsidy* variable remain positive, with a slight change in the significance level and a decrease in the magnitude of the coefficient. Furthermore, the

[60] In addition to one-month lags, four-month moving averages (average of the previous four months) of $License\,Lottery_{it}$ and $License\,Auction_{it}$ are also used as a robustness check, as presented in Table 20 in Appendix A.5.

[61] The coefficient for $Extra\,Subsidy$ is 0.805, which indicates a log increase of the EV market share of 72.2%, thus $e^{0.805} - 1 = 1.2367$.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.0864 | 0.0373 | 0.326*** | 0.246*** | 0.147** | 0.613*** |
| | (0.064) | (0.085) | (0.100) | (0.093) | (0.063) | (0.145) |
| GDP per Capita | -0.00325 | -0.00415 | -0.00255 | -0.00176 | -0.000525 | 0.00303 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Pop Density | -1.584* | -1.285 | -0.981 | -1.272 | -1.279 | -1.180 |
| | (0.816) | (0.855) | (0.811) | (0.779) | (0.792) | (0.854) |
| Charging Pts | -0.00972 | -0.00677 | -0.0130 | -0.0114 | -0.00553 | -0.0175 |
| | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.011) |
| Gas/Electricity | -0.0931 | -0.0893 | -0.0761 | -0.0924 | -0.0933 | -0.0859 |
| | (0.061) | (0.060) | (0.059) | (0.062) | (0.060) | (0.060) |
| Edu Exp R | 1.557 | 2.065 | 7.402 | 0.128 | 1.982 | 4.727 |
| | (4.050) | (4.076) | (4.623) | (4.084) | (4.162) | (4.851) |
| Env Exp R | 8.769 | 8.611 | 8.479 | 26.83* | 9.012 | 25.24** |
| | (10.431) | (10.121) | (9.283) | (13.692) | (9.194) | (12.431) |
| License Lottery (lag) | 1.490*** | 1.470*** | 1.543*** | 1.541*** | 1.380*** | 1.528*** |
| | (0.287) | (0.293) | (0.299) | (0.285) | (0.279) | (0.278) |
| License Auction (lag) | 0.0151** | 0.0135* | 0.0144** | 0.0193** | 0.0130* | 0.0202*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Driving Restriction | 0.245* | 0.247 | 0.289* | 0.174 | 0.312** | 0.272* |
| | (0.147) | (0.149) | (0.147) | (0.155) | (0.144) | (0.159) |
| Extra Subsidy | 1.007*** | 0.986*** | 0.873*** | 0.924*** | 0.942*** | 0.805** |
| | (0.221) | (0.228) | (0.248) | (0.273) | (0.275) | (0.318) |
| Taxi Subsidy | -0.218 | -0.170 | -0.177 | 0.122 | -0.209 | 0.0181 |
| | (0.167) | (0.175) | (0.185) | (0.265) | (0.186) | (0.261) |
| Free Parking | 0.204 | 0.215 | 0.194 | 0.249 | 0.142 | 0.158 |
| | (0.316) | (0.306) | (0.331) | (0.253) | (0.416) | (0.383) |
| Subsidy × GDP per Capita | | 0.000509 | | | | -0.00116* |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.397*** | | | -1.271** |
| | | | (0.479) | | | (0.564) |
| Subsidy × Env Exp R | | | | -5.788* | | -5.200* |
| | | | | (3.043) | | (2.712) |
| Tier=2 × Subsidy | | | | | -0.117*** | -0.103** |
| | | | | | (0.044) | (0.050) |
| Tier=3 × Subsidy | | | | | -0.0904** | -0.0769 |
| | | | | | (0.041) | (0.055) |
| Tier=4 × Subsidy | | | | | -0.145** | -0.119 |
| | | | | | (0.055) | (0.077) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses

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

Note: The corresponding results for $ln(Num/Pop)$ are displayed in Appendix A.8 Table 22 .

Table 8: Adding Extra Incentives, $ln(EV\ share)$

effects of driving restrictions and license plates registration quotas remain almost the same as the ones before introducing the extra incentives.

### 6.3 Difference-in-differences Results

Cities were divided into either the treatment group or the control group, according to their local-to-national subsidy percentages in the last month of 2016.[62] Table 9 shows the results of DID model. The first three columns use the full sample periods from 2016 to 2019. Columns (4) to (6) use data from 2016 to 2018, and columns (7) to (9) use data from 2016 to 2017, one year before and one year after the treatment.

Regressions (1), (4), and (7) use the basic difference-in-differences specification in equation (4) with only the variables $Post17$, $Treat$, and their interaction. We can see that the treatment has a negative and statistically significant impact on EV adoption. The smaller the time window we focus on, the larger the negative effects. However, the difference between the short-term and long-term effects is not large, which is consistent with the changes in total subsidy between the control and the treatment group (see Figure 11 in Appendix A.11). This difference mainly shrank in 2017 but changed little afterward. In regressions (2), (5), and (8), control variables are included; the effects of treatment remain negative and statistically significant, while the coefficients for the controls and restrictions remain similar to those from the previous fixed effects specifications. In regressions (3), (6), and (9), the interactions between $Tier$ and $Post17 * Treat$ are added. Regression (3) shows that the negative effects of treatment are larger for the first-tier cities than for the fourth-tier cities, whereas the differences between first-, second-, and third-tier cities are not significant. This is probably caused by relatively smaller number of cities being treated in the third and fourth tier. Note that in regressions (8) and (9), the variables $License\,Lottery$ and $License\,Auction$ do not have significant coefficients. A possible reason is that people are much more responsive to the negative shock of an abrupt subsidy reduction in the short term when they make a car purchase decision. As a result, the benefits of bypassing the license quota restrictions from purchasing EVs play a less significant role in their purchase decisions.

Alternatively, Table 10 uses treatment intensity instead of the dummy variable for treatment, yielding similar results. The magnitude of the coefficients for $Post17 * Treat\,Intensity$ is larger than that of the corresponding ones in Table 9, implying that, for treatment group

[62] A few cities had a higher than 50% local-to-national subsidy percentage one or two months before 2017 but not in December 2016; when moving these cities from the control group to the treatment group, the trends of the deseasonalized mean of $ln(EV\,share)$ and the results of the DID regressions are very similar.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Post17*Treat | -0.383* | -0.427** | -0.628*** | -0.422** | -0.434** | -0.550** | -0.427** | -0.458** | -0.558** |
| | (0.197) | (0.206) | (0.216) | (0.196) | (0.201) | (0.210) | (0.188) | (0.197) | (0.229) |
| License Lottery (lag) | | 1.537*** | 1.507*** | | 2.669*** | 2.596** | | -11.52 | -5.528 |
| | | (0.313) | (0.309) | | (0.989) | (0.999) | | (41.043) | (44.198) |
| License Auction (lag) | | 0.0161** | 0.0177** | | 0.0172* | 0.0181* | | 0.0141 | 0.0147 |
| | | (0.008) | (0.008) | | (0.010) | (0.010) | | (0.015) | (0.016) |
| Driving Restriction | | 0.244* | 0.262* | | 0.434** | 0.446** | | 0.876* | 0.886** |
| | | (0.142) | (0.138) | | (0.200) | (0.198) | | (0.443) | (0.431) |
| Tier=2 × Post17*Treat | | | 0.308 | | | 0.215 | | | 0.158 |
| | | | (0.302) | | | (0.295) | | | (0.310) |
| Tier=3 × Post17*Treat | | | 0.365 | | | 0.148 | | | 0.166 |
| | | | (0.316) | | | (0.326) | | | (0.366) |
| Tier=4 × Post17*Treat | | | 0.330* | | | 0.124 | | | 0.217 |
| | | | (0.196) | | | (0.193) | | | (0.197) |
| Controls | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample Periods | 2016-2019 | 2016-2019 | 2016-2019 | 2016-2018 | 2016-2018 | 2016-2018 | 2016-2017 | 2016-2017 | 2016-2017 |
| Observations | 3945 | 3605 | 3605 | 2902 | 2746 | 2746 | 1862 | 1706 | 1706 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: DID Results for $ln(EV\ share)$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Post17*Treat Intensity | -0.472** | -0.511** | -0.762*** | -0.518** | -0.532** | -0.682*** | -0.528** | -0.550** | -0.666*** |
| | (0.219) | (0.231) | (0.211) | (0.220) | (0.226) | (0.206) | (0.212) | (0.227) | (0.234) |
| License Lottery (lag) | | 1.491*** | 1.466*** | | 2.460** | 2.432** | | -13.71 | -6.192 |
| | | (0.306) | (0.296) | | (1.022) | (0.994) | | (41.120) | (44.574) |
| License Auction (lag) | | 0.0161** | 0.0180** | | 0.0166* | 0.0178* | | 0.0135 | 0.0140 |
| | | (0.007) | (0.008) | | (0.010) | (0.010) | | (0.015) | (0.016) |
| Driving Restriction | | 0.256* | 0.275** | | 0.447** | 0.463** | | 0.894** | 0.909** |
| | | (0.140) | (0.134) | | (0.198) | (0.195) | | (0.428) | (0.415) |
| Tier=2 × Post17*Treat Intensity | | | 0.430 | | | 0.321 | | | 0.216 |
| | | | (0.354) | | | (0.349) | | | (0.368) |
| Tier=3 × Post17*Treat Intensity | | | 0.396 | | | 0.131 | | | 0.127 |
| | | | (0.329) | | | (0.320) | | | (0.396) |
| Tier=4 × Post17*Treat Intensity | | | 0.453** | | | 0.245 | | | 0.315 |
| | | | (0.186) | | | (0.187) | | | (0.200) |
| Controls | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample Periods | 2016-2019 | 2016-2019 | 2016-2019 | 2016-2018 | 2016-2018 | 2016-2018 | 2016-2017 | 2016-2017 | 2016-2017 |
| Observations | 3945 | 3605 | 3605 | 2902 | 2746 | 2746 | 1862 | 1706 | 1706 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: DID Results for $ln(EV\ share)$, using treatment intensity

cities, higher local-to-national subsidy percentages before the introduction of the new policy lead to larger decreases in EV adoption after the policy.

To further check the validity of the results, several supplemental analyses are conducted, which are presented in Appendix A.11. First, I aggregate the monthly data at the quarter level, checking the parallel trends graphically, and re-producing the regression results. Second, I relax the condition for the treatment group, also including cities with higher than 50% local-to-national subsidy percentages before December 2016 (5 cities move from the control to the treatment group); the trends and regression results do not change much. Lastly, I conduct placebo tests using different time points (January 2018 and January 2019) as the start of treatment, with the results showing no significant coefficient for the placebo variable $Post * Treat$.

Using the 2017 restriction on local subsidies, the results of the difference-in-differences analysis show that reducing subsidies decreased EV market share, which provides evidence that subsidies do promote EV adoption.

# 7 Robustness Checks

## 7.1 Results for BEVs Only

Table 11 presents the results for BEVs only. The dependent variable is $ln(BEV\,share)$, and the variable of interest is $Subsidy\,(BEV)$, which is the average subsidy value for BEVs. Column (1) presents the results for the baseline model, being equivalent to column (1) in Table 6. Column (2) adds the three extra incentives, and columns (3) - (7) are equivalent to columns (2) - (6) in Table 6 when only including BEVs in the analysis; column (8) combines the extra incentives with the interaction terms. The corresponding results for $ln(Num/Pop)$ are displayed in Appendix A.9.

Compared to the results for EVs (including PHEVs and BEVs), subsidy effects are still positive and statistically significant, having a similar magnitude on average. From regression (6) we can see that, on average, the subsidy effects are still the largest for first-tier cities, while their magnitude decreases for second-, third- and fourth-tier cities. However, when including the interactions (column (7)) and the extra incentives (column (8)), we do not see heterogeneous subsidy effects across the different city tiers. The only significant coefficient for the interaction terms is the one for $Edu\,Exp\,R$, which indicates that the differences between the subsidy effects across tiers are mainly due to the share of government expenditures allocated to education.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Subsidy (BEV) | 0.0756 | 0.0555 | -0.00754 | 0.376*** | 0.188** | 0.118* | 0.539*** | 0.485*** |
| | (0.064) | (0.065) | (0.090) | (0.095) | (0.085) | (0.064) | (0.168) | (0.167) |
| GDP per Capita | 0.00574 | 0.00530 | 0.00513 | 0.00800 | 0.00698 | 0.00869 | 0.0108* | 0.00944 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) | (0.006) | (0.006) |
| Edu Exp R | 4.428 | 4.776 | 5.054 | 12.05*** | 3.239 | 4.957 | 10.35** | 10.08** |
| | (4.078) | (4.024) | (4.106) | (4.512) | (4.100) | (4.203) | (4.737) | (4.704) |
| Env Exp R | 16.40 | 17.02 | 16.49 | 16.32* | 30.59** | 16.87 | 29.14** | 30.35** |
| | (11.051) | (11.067) | (10.527) | (9.597) | (13.604) | (10.160) | (12.294) | (13.613) |
| License Lottery (lag) | 1.425*** | 1.438*** | 1.393*** | 1.490*** | 1.468*** | 1.376*** | 1.515*** | 1.509*** |
| | (0.327) | (0.328) | (0.338) | (0.344) | (0.330) | (0.366) | (0.367) | (0.353) |
| License Auction (lag) | 0.0169** | 0.0173** | 0.0139 | 0.0162** | 0.0197** | 0.0145* | 0.0198** | 0.0206** |
| | (0.008) | (0.008) | (0.009) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) |
| Driving Restriction | 0.327** | 0.331** | 0.333** | 0.380** | 0.282* | 0.401*** | 0.366** | 0.345** |
| | (0.144) | (0.151) | (0.146) | (0.147) | (0.151) | (0.150) | (0.161) | (0.168) |
| Extra Subsidy | | 1.064*** | | | | | | 0.844** |
| | | (0.282) | | | | | | (0.352) |
| Taxi Subsidy | | -0.256 | | | | | | 0.00163 |
| | | (0.167) | | | | | | (0.279) |
| Free Parking | | -0.0238 | | | | | | -0.0329 |
| | | (0.567) | | | | | | (0.570) |
| Subsidy (BEV) × GDP per Capita | | | 0.000873* | | | | -0.000625 | -0.000479 |
| | | | (0.001) | | | | (0.001) | (0.001) |
| Subsidy (BEV) × Edu Exp R | | | | -1.734*** | | | -1.627*** | -1.477*** |
| | | | | (0.435) | | | (0.523) | (0.531) |
| Subsidy (BEV) × Env Exp R | | | | | -4.201 | | -3.759 | -3.969 |
| | | | | | (2.635) | | (2.320) | (2.751) |
| Tier=2 × Subsidy (BEV) | | | | | | -0.0751 | -0.0422 | -0.0385 |
| | | | | | | (0.047) | (0.050) | (0.052) |
| Tier=3 × Subsidy (BEV) | | | | | | -0.0804* | -0.0361 | -0.0241 |
| | | | | | | (0.043) | (0.059) | (0.061) |
| Tier=4 × Subsidy (BEV) | | | | | | -0.136** | -0.0724 | -0.0601 |
| | | | | | | (0.057) | (0.080) | (0.083) |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3450 | 3450 | 3450 | 3450 | 3450 | 3450 | 3450 | 3450 |

Standard errors in parentheses

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

Note: The corresponding results for $ln(Num/Pop)$ are displayed in Appendix A.9.

Table 11: Results for $ln(BEV\ share)$

## 7.2 Dummy for Subsidy and Quarterly Data

In Table 12, the total subsidy amount is replaced by $Sub\,Dummy$, a dummy indicating the existence or absence of local subsidies[63] in city $i$ at time $t$, regardless of the subsidy amount. Using the dummy variable rather than the subsidy amount helps to reduce measurement error. The first two columns show the results without the interaction terms, wherein the coefficients for $Sub\,Dummy$ are positive but not statistically significant. After allowing for heterogeneous subsidy effects (i.e., including interactions), the coefficient for $Sub\,Dummy$ becomes positive and statistically significant. Given that $Sub\,Dummy$ does not differentiate different subsidy amounts, its coefficient measures the average difference between observations with and without local subsidies. The results are consistent with the ones using subsidy amount in the previous section, although the magnitudes of the coefficients are not comparable.

Additionally, to alleviate the potential inaccuracy issue due to the timing of policy implementation, I aggregate the monthly EV share data into quarterly figures. The results are displayed in Table 13, and are quite similar to the ones using monthly data.

## 7.3 Results including the Lags of the Dependent Variable

As shown in Table 14, when including a one-month lag and a two-month lag of the dependent variable, $ln(EV\,share)$, the coefficient for $Subsidy$ remains significant and positive, with a slight change in its magnitude.[64] Subsidies still have the largest effect in first-tier cities, and their effects are generally decreasing in the other city tiers except for the third-tier cities in regression (3) to (6). The shares of government expenditure allocated to education and environmental protection still negatively impact the subsidy effect. GDP per capita is also negatively associated with the subsidy effect, but loses statistical significance when including both the one-month and two-month lags. The lagged dependent variables each lead to positive and statistically significant coefficients, indicating the presence of network effects/-positive externalities of EVs. Since a higher EV share would indicate a higher probability of seeing them on the road or knowing someone who owned an EV, this will probably result in an increase in EV adoption later on.

[63]National subsidies were offered to all cities starting from January 2016, so there would be no variation in the sample period if we used a dummy variable to reflect national subsidies.

[64]Results using the Arellano-Bond estimator are presented in Appendix A.10.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sub Dummy | 0.216 | 0.155 | 0.666*** | 0.517*** | 2.481*** | 2.195*** |
| | (0.135) | (0.142) | (0.142) | (0.174) | (0.708) | (0.732) |
| License Lottery (lag) | 1.496*** | 1.499*** | 1.488*** | 1.497*** | 1.584*** | 1.588*** |
| | (0.281) | (0.278) | (0.310) | (0.307) | (0.309) | (0.305) |
| License Auction (lag) | 0.0144* | 0.0150** | 0.0102 | 0.0115 | 0.0161** | 0.0169** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) |
| Driving Restriction | 0.216 | 0.229 | 0.238* | 0.246* | 0.203 | 0.206 |
| | (0.148) | (0.144) | (0.142) | (0.141) | (0.151) | (0.151) |
| Extra Subsidy | | 0.994*** | | 0.857*** | | 0.862** |
| | | (0.214) | | (0.293) | | (0.334) |
| Taxi Subsidy | | -0.177 | | -0.222 | | -0.231 |
| | | (0.171) | | (0.202) | | (0.229) |
| Free Parking | | 0.224 | | 0.168 | | 0.198 |
| | | (0.325) | | (0.386) | | (0.349) |
| Sub Dummy × GDP per Capita | | | | | -0.00128 | -0.000274 |
| | | | | | (0.003) | (0.003) |
| Sub Dummy × Edu Exp R | | | | | -6.788** | -6.326* |
| | | | | | (3.344) | (3.369) |
| Sub Dummy × Env Exp R | | | | | -23.23* | -24.93* |
| | | | | | (13.659) | (13.937) |
| Tier=2 × Sub Dummy | | | -0.448** | -0.356* | -0.281 | -0.172 |
| | | | (0.191) | (0.205) | (0.213) | (0.232) |
| Tier=3 × Sub Dummy | | | -0.437* | -0.319 | -0.206 | -0.0529 |
| | | | (0.222) | (0.240) | (0.315) | (0.337) |
| Tier=4 × Sub Dummy | | | -0.853*** | -0.724*** | -0.532 | -0.354 |
| | | | (0.251) | (0.266) | (0.379) | (0.403) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses

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

Note: The corresponding results for $ln(Num/Pop)$ are displayed in Appendix A.12.

Table 12: Dummy for Local Subsidy, $ln(EV\ share)$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.123* | 0.197*** | 0.708*** | 0.105 | 0.176*** | 0.666*** |
| | (0.065) | (0.064) | (0.143) | (0.067) | (0.067) | (0.146) |
| License Lottery (lag) | 1.543*** | 1.375*** | 1.589*** | 1.539*** | 1.371*** | 1.573*** |
| | (0.203) | (0.217) | (0.219) | (0.203) | (0.212) | (0.213) |
| License Auction (lag) | 0.0184** | 0.0158** | 0.0242*** | 0.0187** | 0.0165** | 0.0248*** |
| | (0.009) | (0.007) | (0.007) | (0.009) | (0.007) | (0.007) |
| Driving Restriction | 0.240 | 0.321** | 0.293* | 0.254 | 0.321** | 0.288* |
| | (0.157) | (0.141) | (0.149) | (0.155) | (0.140) | (0.153) |
| Extra Subsidy | | | | 0.913*** | 0.830*** | 0.714** |
| | | | | (0.239) | (0.307) | (0.356) |
| Taxi Subsidy | | | | -0.277 | -0.272 | -0.0850 |
| | | | | (0.199) | (0.217) | (0.277) |
| Free Parking | | | | 0.0474 | -0.0265 | -0.0286 |
| | | | | (0.265) | (0.401) | (0.398) |
| Subsidy × GDP per Capita | | | -0.00148** | | | -0.00139** |
| | | | (0.001) | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.420*** | | | -1.328** |
| | | | (0.530) | | | (0.531) |
| Subsidy × Env Exp R | | | -4.763** | | | -4.716* |
| | | | (2.089) | | | (2.374) |
| Tier=2 × Subsidy | | -0.133*** | -0.127*** | | -0.130*** | -0.123** |
| | | (0.043) | (0.047) | | (0.042) | (0.047) |
| Tier=3 × Subsidy | | -0.124*** | -0.117** | | -0.111*** | -0.106* |
| | | (0.040) | (0.053) | | (0.041) | (0.054) |
| Tier=4 × Subsidy | | -0.162*** | -0.147** | | -0.149*** | -0.138* |
| | | (0.051) | (0.069) | | (0.052) | (0.072) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City FE & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 1269 | 1269 | 1269 | 1269 | 1269 | 1269 |

Standard errors in parentheses

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

Note: The corresponding results for $ln(Num/Pop)$ are displayed in Appendix A.13.

Table 13: Quarterly Data, $ln(EV\ share)$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.0988*** | 0.0815** | 0.432*** | 0.374*** | 0.400*** | 0.346*** |
| | (0.037) | (0.037) | (0.082) | (0.078) | (0.084) | (0.080) |
| 1-lag of ln(EV share) | 0.457*** | 0.410*** | 0.449*** | 0.404*** | 0.445*** | 0.402*** |
| | (0.024) | (0.023) | (0.024) | (0.023) | (0.024) | (0.023) |
| 2-lag of ln(EV share) | | 0.122*** | | 0.117*** | | 0.115*** |
| | | (0.018) | | (0.017) | | (0.018) |
| License Lottery (lag) | 0.844*** | 0.761*** | 0.959*** | 0.865*** | 0.957*** | 0.865*** |
| | (0.174) | (0.135) | (0.178) | (0.139) | (0.171) | (0.132) |
| License Auction (lag) | 0.00915** | 0.00877*** | 0.0135*** | 0.0124*** | 0.0139*** | 0.0128*** |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) |
| Driving Restriction | 0.144* | 0.0994* | 0.133* | 0.0834 | 0.128 | 0.0779 |
| | (0.072) | (0.056) | (0.079) | (0.063) | (0.082) | (0.065) |
| Extra Subsidy | | | | | 0.455** | 0.407** |
| | | | | | (0.197) | (0.196) |
| Taxi Subsidy | | | | | -0.0436 | -0.0147 |
| | | | | | (0.164) | (0.156) |
| Free Parking | | | | | 0.155 | 0.109 |
| | | | | | (0.237) | (0.217) |
| Subsidy × GDP per Capita | | | -0.000805** | -0.000586 | -0.000728* | -0.000507 |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Subsidy × Edu Exp R | | | -1.099*** | -0.998*** | -1.022*** | -0.928*** |
| | | | (0.305) | (0.291) | (0.312) | (0.295) |
| Subsidy × Env Exp R | | | -2.738** | -2.664** | -2.763* | -2.744** |
| | | | (1.262) | (1.015) | (1.456) | (1.183) |
| Tier=2 × Subsidy | -0.0690*** | -0.0651*** | -0.0557* | -0.0496* | -0.0538* | -0.0476* |
| | (0.026) | (0.023) | (0.028) | (0.026) | (0.029) | (0.026) |
| Tier=3 × Subsidy | -0.0607** | -0.0587** | -0.0445 | -0.0383 | -0.0372 | -0.0316 |
| | (0.025) | (0.025) | (0.032) | (0.032) | (0.033) | (0.033) |
| Tier=4 × Subsidy | -0.0964*** | -0.105*** | -0.0724* | -0.0751* | -0.0654 | -0.0680 |
| | (0.033) | (0.033) | (0.042) | (0.041) | (0.043) | (0.041) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3501 | 3347 | 3501 | 3347 | 3501 | 3347 |

Standard errors in parentheses

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

Note: The corresponding results for $ln(Num/Pop)$ are displayed in Appendix A.14

Table 14: Including the Lags of Dependent Variable, $ln(EV\ share)$

# 8 Conclusion

This study provides a fixed effects analysis of the factors that promote EV adoption in China, focusing on EV subsidies and exemptions from two vehicle ownership and use restrictions. The findings indicate that while EV subsidies have a positive effect on EV adoption, this effect is heterogeneous and depends on several factors, such as tier of the city, GDP per capita, and the shares of government expenditure allocated to education or environmental protection. The analysis reveals that the largest effects of EV subsidies are observed in first-tier cities, where an increase of 10,000 RMB in subsidies leads to an average increase in EV market share of approximately 18.77%. However, for cities in the other tiers, the effects are much smaller, ranging from 0.7% to 6.2% for every 10,000 RMB increase in subsidy. These results highlight the importance of considering the level of development of a city when designing EV subsidy policies. Additionally, results show that an increase of 1,000 RMB in GDP per capita reduces the effect of subsidies by 0.116 percentage points. Moreover, the effects of subsidies are lower by 1.352 and 4.591 percentage points for every 1 percentage point increase in the share of government expenditure allocated to education and environmental protection, respectively. Furthermore, subsidies specifically targeting charging facilities and electricity fees have a positive impact on EV adoption, but the limited availability of these subsidies warrants further investigation.

This study also reveals several key findings regarding the impact of exemptions from license plate quotas and driving restrictions on EV adoption. The analysis shows that both of these policy instruments have relatively large and statistically significant positive effects on EV adoption. Specifically, the results indicate that during the sample period (2016-2019), a significant number of people purchased EVs to circumvent these restrictions, with driving restrictions and license plate quotas leading to 30.87% and 222.20% increases in the EV market share, respectively. These results suggest that policies that restrict the use of ICEVs or provide exemptions to EV users may be more effective in promoting EV adoption than subsidies.

To further investigate the relationship between license plate quotas and EV adoption, additional analysis is conducted using the probability of winning a lottery and the average auction price of an ICEV license plate. The findings show that a 1 percentage point decrease in the probability of winning a lottery is associated with a 1.378% increase in EV market share, while a 1,000 RMB increase in the auction price is correlated with a 1.22% increase in EV market share. These results suggest that the effectiveness of license plate quotas in promoting EV adoption is greater when it is more costly to acquire an ICEV license plate.

In addition to the fixed effects regressions, a difference-in-differences analysis is conducted to exploit the 2017 policy that abruptly affected nearly half of the sampled cities. The DID analysis reveals that the sudden reduction in local subsidies led to a significant decrease in EV adoption, suggesting a positive causal effect of subsidies. These findings provide additional support for the main results.

The implications of the findings extend beyond this study's specific context in China to other countries facing similar challenges. The results suggest that providing subsidies to EV buyers can be an effective policy tool to promote EV adoption, although the magnitude of the impact varies across cities. When designing a subsidy scheme, policymakers should consider a region's financial and economic context, including the tier of the city, as well as its investments in education and potential attitudes towards environmentalism. Additionally, non-financial policy instruments such as restrictions on ICEVs may be even more effective, and should be carefully considered alongside financial incentives. This study thus provides important insights for policymakers seeking to encourage the widespread adoption of EVs as a key component of sustainable transportation systems.

Future research should aim to further strengthen the results through more nuanced and comprehensive measurements for some factors. One promising avenue for improvement could involve constructing a better measurement of environmentalism that more accurately reflects people's attitudes towards environmental protection. For example, one potential approach would be to employ text analysis methods to capture and assess social media discussions related to environmentalism, or to investigate the frequency of related words used in local news coverage. Another example is to construct a more detailed measurement of the availability of charging facilities, which could involve gathering more comprehensive data on the number, location, and accessibility of charging stations, as well as their charging speeds and pricing structures. These better measurements could enhance our understanding of the factors that influence EV adoption.

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# A Appendix

## A.1 Summary Statistics by Year

| | Mean | S.D. | Min | Median | Max |
|---|---|---|---|---|---|
| **2016** | | | | | |
| EV share | 0.01 | 0.03 | 0.00 | 0.00 | 0.32 |
| Num/Pop (number/thousand people) | 0.03 | 0.10 | 0.00 | 0.00 | 1.33 |
| Local subsidy ratio | 0.60 | 0.41 | 0.00 | 0.74 | 1.06 |
| Subsidy (in 10 thousand RMB) | 6.19 | 1.58 | 3.88 | 6.74 | 7.98 |
| GDP per capita (1,000) | 76.13 | 33.22 | 24.12 | 72.35 | 172.45 |
| Pop density (thousand people/$km^2$) | 0.80 | 0.87 | 0.06 | 0.60 | 5.96 |
| Charging points (1,000) | 4.81 | 5.47 | 0.02 | 2.22 | 21.94 |
| Gas price (RMB/ton) | 5.43 | 0.21 | 4.95 | 5.42 | 5.89 |
| Electricity price (RMB/kWh) | 0.78 | 0.08 | 0.54 | 0.80 | 0.91 |
| Gas/Electricity price | 7.03 | 0.86 | 5.47 | 6.81 | 10.58 |
| Govt. edu expenditure ratio | 0.18 | 0.04 | 0.10 | 0.18 | 0.27 |
| Govt. env expenditure ratio | 0.03 | 0.01 | 0.02 | 0.03 | 0.06 |
| Driving restriction (0 or 1) | 0.13 | 0.34 | 0.00 | 0.00 | 1.00 |
| License restriction (0 or 1) | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 |
| License lottery: 1 - probability of winning | 0.92 | 0.26 | 0.00 | 1.00 | 1.00 |
| License auction price (in 1,000 RMB) | 2.75 | 12.00 | 0.00 | 0.00 | 88.67 |
| Extra subsidy dummy for charging/electricity (0 or 1) | 0.03 | 0.16 | 0.00 | 0.00 | 1.00 |
| EV Taxi subsidy dummy (0 or 1) | 0.07 | 0.25 | 0.00 | 0.00 | 1.00 |
| Free parking dummy (0 or 1) | 0.02 | 0.14 | 0.00 | 0.00 | 1.00 |
| **2017** | | | | | |
| EV share | 0.02 | 0.04 | 0.00 | 0.00 | 0.39 |
| Num/Pop (number/thousand people) | 0.05 | 0.14 | 0.00 | 0.01 | 1.38 |
| Local subsidy ratio | 0.43 | 0.33 | 0.00 | 0.50 | 1.00 |
| Subsidy (in 10 thousand RMB) | 4.43 | 1.03 | 3.10 | 4.65 | 6.20 |
| GDP per capita (1,000) | 80.90 | 35.70 | 26.37 | 78.37 | 183.54 |
| Pop density (thousand people/$km^2$) | 0.80 | 0.90 | 0.06 | 0.60 | 6.27 |
| Charging points (1,000) | 8.81 | 8.38 | 0.09 | 5.38 | 30.36 |
| Gas price (RMB/ton) | 5.89 | 0.21 | 5.54 | 5.87 | 6.42 |
| Electricity price (RMB/kWh) | 0.77 | 0.08 | 0.54 | 0.79 | 0.91 |
| Gas/Electricity price | 7.76 | 0.97 | 6.11 | 7.48 | 11.07 |
| Govt. edu expenditure ratio | 0.18 | 0.03 | 0.11 | 0.18 | 0.25 |
| Govt. env expenditure ratio | 0.03 | 0.01 | 0.02 | 0.03 | 0.07 |
| Driving Restriction (0 or 1) | 0.15 | 0.36 | 0.00 | 0.00 | 1.00 |
| License restriction (0 or 1) | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 |
| License lottery: 1 - probability of winning | 0.92 | 0.27 | 0.00 | 1.00 | 1.00 |
| License auction price (in 1,000 RMB) | 3.09 | 13.28 | 0.00 | 0.00 | 93.54 |
| Extra subsidy dummy for charging/electricity (0 or 1) | 0.04 | 0.19 | 0.00 | 0.00 | 1.00 |
| EV Taxi subsidy dummy (0 or 1) | 0.08 | 0.27 | 0.00 | 0.00 | 1.00 |
| Free parking dummy (0 or 1) | 0.03 | 0.16 | 0.00 | 0.00 | 1.00 |

| | Mean | S.D. | Min | Median | Max |
|---|---|---|---|---|---|
| **2018** | | | | | |
| EV share | 0.03 | 0.05 | 0.00 | 0.01 | 0.45 |
| Num/Pop (number/thousand people) | 0.08 | 0.17 | 0.00 | 0.02 | 2.36 |
| Local subsidy ratio | 0.26 | 0.25 | 0.00 | 0.25 | 1.00 |
| Subsidy (in 10 thousand RMB) | 3.99 | 0.80 | 3.17 | 3.96 | 6.34 |
| GDP per capita (1,000) | 82.76 | 37.67 | 27.13 | 77.10 | 189.57 |
| Pop density (thousand people/$km^2$) | 0.76 | 0.90 | 0.06 | 0.58 | 6.52 |
| Charging points (1,000) | 12.11 | 11.06 | 0.23 | 7.94 | 42.13 |
| Gas price (RMB/ton) | 6.67 | 0.32 | 6.10 | 6.68 | 7.42 |
| Electricity price (RMB/kWh) | 0.74 | 0.09 | 0.52 | 0.75 | 0.91 |
| Gas/Electricity price | 9.19 | 1.33 | 6.80 | 8.92 | 14.25 |
| Govt. edu expenditure ratio | 0.17 | 0.03 | 0.11 | 0.17 | 0.26 |
| Govt. env expenditure ratio | 0.03 | 0.01 | 0.01 | 0.03 | 0.06 |
| Driving Restriction (0 or 1) | 0.20 | 0.40 | 0.00 | 0.00 | 1.00 |
| License restriction (0 or 1) | 0.08 | 0.28 | 0.00 | 0.00 | 1.00 |
| License lottery: 1 - probability of winning | 0.93 | 0.25 | 0.00 | 1.00 | 1.00 |
| License auction price (in 1,000 RMB) | 2.94 | 13.19 | 0.00 | 0.00 | 95.10 |
| Extra subsidy dummy for charging/electricity (0 or 1) | 0.04 | 0.21 | 0.00 | 0.00 | 1.00 |
| EV Taxi subsidy dummy (0 or 1) | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 |
| Free parking dummy (0 or 1) | 0.02 | 0.15 | 0.00 | 0.00 | 1.00 |
| **2019** | | | | | |
| EV share | 0.03 | 0.05 | 0.00 | 0.02 | 0.34 |
| Num/Pop (number/thousand people) | 0.07 | 0.13 | 0.00 | 0.02 | 1.13 |
| Local subsidy ratio | 0.14 | 0.22 | 0.00 | 0.00 | 1.00 |
| Subsidy (in 10 thousand RMB) | 1.31 | 1.12 | 0.00 | 1.77 | 3.54 |
| GDP per capita (1,000) | 88.73 | 40.83 | 28.38 | 84.25 | 203.49 |
| Pop density (thousand people/$km^2$) | 0.78 | 0.92 | 0.06 | 0.59 | 6.73 |
| Charging points (1,000) | 19.08 | 16.26 | 0.67 | 14.55 | 58.02 |
| Gas price (RMB/ton) | 6.26 | 0.17 | 6.04 | 6.21 | 6.67 |
| Electricity price (RMB/kWh) | 0.69 | 0.09 | 0.40 | 0.70 | 0.90 |
| Gas/Electricity price | 9.24 | 1.30 | 6.75 | 9.10 | 15.89 |
| Govt. edu expenditure ratio | 0.17 | 0.03 | 0.11 | 0.18 | 0.25 |
| Gov env expenditure ratio | 0.04 | 0.01 | 0.02 | 0.03 | 0.07 |
| Driving Restriction (0 or 1) | 0.25 | 0.44 | 0.00 | 0.00 | 1.00 |
| License restriction (0 or 1) | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 |
| License lottery: 1 - probability of winning | 0.92 | 0.26 | 0.00 | 1.00 | 1.00 |
| License auction price (in 1,000 RMB) | 2.73 | 12.48 | 0.00 | 0.00 | 90.12 |
| Extra subsidy dummy for charging/electricity (0 or 1) | 0.03 | 0.18 | 0.00 | 0.00 | 1.00 |
| EV Taxi subsidy dummy (0 or 1) | 0.07 | 0.26 | 0.00 | 0.00 | 1.00 |
| Free parking dummy (0 or 1) | 0.02 | 0.14 | 0.00 | 0.00 | 1.00 |

Table 15: Summary Statistics by Year

## A.2 Description of the City Tiers System

| Tier | Cities<br>(Notes: because many cities in China have names that appear identical in Pinyin,<br>the list below includes city names written in Chinese characters to help differentiate them) | Number of cities |
|---|---|---|
| Tier 1 | Beijing, Shanghai, Guangzhou, Shenzhen<br>北京市、上海市、广州市、深圳市 | 4 (out of 4) |
| New Tier 1 | Chengdu, Chongqing, Hangzhou, Wuhan, Nanjing, Tianjin, Suzhou, Xi'an, Changsha,<br>Shenyang, Qingdao, Zhengzhou, Dalian, Dongguan, Ningbo<br>成都市、重庆市、杭州市、武汉市、南京市、天津市、苏州市、西安市、长沙市、<br>沈阳市、青岛市、郑州市、大连市、东莞市、宁波市 | 15 (out of 15) |
| Tier 2 | Xiamen, Fuzhou, Wuxi, Hefei, Kunming, Harbin, Jinan, Foshan, Changchun,<br>Wenzhou, Shijiazhuang, Nanning, Changzhou, Quanzhou, Nanchang, Guiyang, Taiyuan,<br>Yantai, Jiaxing, Nantong, Jinhua, Zhuhai, Huizhou, Xuzhou, Haikou, Ürümqi,<br>Shaoxing, Zhongshan, Taizhou, Lanzhou<br>厦门市、福州市、无锡市、合肥市、昆明市、哈尔滨市、济南市、佛山市、长春市、<br>温州市、石家庄市、南宁市、常州市、泉州市、南昌市、贵阳市、太原市、<br>烟台市、嘉兴市、南通市、金华市、珠海市、惠州市、徐州市、海口市、乌鲁木齐市、<br>绍兴市、中山市、台州市、兰州市 | 23 (out of 30) |
| Tier 3 | Weifang, Baoding, Zhenjiang, Yangzhou, Guilin, Tangshan, Sanya, Huzhou, Hohhot,<br>Langfang, Luoyang, Weihai, Yancheng, Linyi, Jiangmen, Shantou, Taizhou, Zhangzhou,<br>Handan, Jining, Wuhu, Zibo, Yinchuan, Liuzhou, Mianyang, Zhanjiang, Anshan,<br>Ganzhou, Daqing, Yichang, Baotou, Xianyang, Qinhuangdao, Zhuzhou, Putian, Jilin,<br>Huai'an, Zhaoqing, Ningde, Hengyang, Nanping, Lianyungang, Dandong, Lijiang, Jieyang,<br>Yanbian Korean Autonomous Prefecture, Zhoushan, Jiujiang, Longyan, Cangzhou, Fushun,<br>Xiangyang, Shangrao, Yingkou, Sanming, Bengbu, Lishui, Yueyang, Qingyuan, Jingzhou,<br>Tai'an, Quzhou, Panjin, Dongying, Nanyang, Ma'anshan, Nanchong, Xining, Xiaogan,<br>Qiqihar<br>潍坊市、保定市、镇江市、扬州市、桂林市、唐山市、三亚市、湖州市、呼和浩特市、<br>廊坊市、洛阳市、威海市、盐城市、临沂市、江门市、汕头市、泰州市、漳州市、<br>邯郸市、济宁市、芜湖市、淄博市、银川市、柳州市、绵阳市、湛江市、鞍山市、<br>赣州市、大庆市、宜昌市、包头市、咸阳市、秦皇岛市、株洲市、莆田市、吉林市、<br>淮安市、肇庆市、宁德市、衡阳市、南平市、连云港市、丹东市、丽江市、揭阳市、<br>延边朝鲜族自治州、舟山市、九江市、龙岩市、沧州市、抚顺市、<br>襄阳市、上饶市、营口市、三明市、蚌埠市、丽水市、岳阳市、清远市、荆州市、<br>泰安市、衢州市、盘锦市、东营市、南阳市、马鞍山市、南充市、西宁市、孝感市、<br>齐齐哈尔市 | 28 (out of 71) |
| Tiers 4 & 5 | Anshun, Bijie, Chengde, Dali, Hengshui, Jincheng, Liaocheng, Liupanshui, Luzhou,<br>Pingxiang, Qiandongnan, Xingtai, Xinxiang, Yichun, Yuxi, Zhangjiakou, Zunyi, ...<br>安顺、毕节、承德、大理、衡水、晋城、聊城、六盘水、泸州、<br>萍乡、黔东南、邢台、新乡、宜春、玉溪、张家口、遵义、…… | 17 (out of 219) |

Note: The cities in black are the 87 cities included in the data. The cities in gray were not included in the analysis; moreover, the list of tier 4 & 5 cities is not complete due to the large numbers of cities in these two tiers. Among the cities in tiers 4 and 5, the underlined ones are in tier 5. From https://www.yicai.com/

Table 16: 2017 List of Cities in the Different Tiers

According to the report, cities are evaluated on five factors: concentration of commercial resources, extent to which a city serves as a commercial hub, vitality of urban residents, diversity of lifestyles, and future flexibility. The ranking scores are obtained by using the Expert Grading Method and principal component analysis method after collecting data from 170 mainstream consumer brands commercial stores and 18 leading Internet companies in various fields, as well as big data from data agencies.

## A.3 Cities with Extra Incentives

| City | Extra Subsidy | Taxi Subsidy | Free Parking | Details | Tier |
|---|---|---|---|---|---|
| Xi'an | 2014.09 | | 2014.09 | (1) 10,000 RMB additional subsidy for an individual charging facility installation and electricity fees.<br>(2) 2-hour/day free parking in public parking lots. | 1 |
| Hefei | 2014.12 | | 2018.01 | (1) 10,000 RMB additional subsidy for an individual charging facility installation and electricity fees.<br>(2) Free 2-hour/day street parking, and twice per day, 5 hours each time free parking in state-owned parking lots. | 2 |
| Zhengzhou | 2016.12 | 2016.12 | 2019.05 | (1) 10,000 RMB (BEV) or 5,000 RMB (PHEV) additional subsidy for insurance, toll, charging facility installation, and electricity fees.<br>(2) 30,000 RMB extra subsidy for EV taxi.<br>(3) Half-price parking and free street parking from 8pm-8am. | 1 |
| Putian | 2018.02 | | 2018.03 | (1) 1,500 RMB additional subsidy for electricity fees.<br>(2) 3-hour/day free parking in state-owned parking lots. | 3 |
| Handan | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 3 |
| Baoding | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 3 |
| Xingtai | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 4 |
| Langfang | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 3 |
| Cangzhou | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 3 |
| Zhangjiakou | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 4 |
| Hengshui | | 2015.12 | | Local subsidy (1:1 national subsidy) for EV taxis.<br>No local subsidy for private use EVs. | 4 |
| Kunming | | | 2016.07 | 2-hour/day free parking in state-owned parking lots. | 2 |
| Nanjing | | | 2016.07 | 1-hour/day free street parking. | 1 |
| Yangzhou | | | 2017.12 | 1-hour/day free parking in designated parking lots. | 3 |
| Taiyuan | | | 2014.08 | 2-hour/day free street parking and reduced fees in public parking lots. | 2 |
| Shenzhen | | | 2016.09 | 1-hour/day free street parking. Starting from 2017.12, 2-hour free parking in designated parking lots. | 1 |
| Chengdu | | | 2016.02 | 2-hour/day free street parking. | 1 |
| Nantong | | | 2018.04 | Half-price parking in designated parking lots and street parking. | 2 |
| Shenyang | | | 2018.11 | Half-price parking in state-owned parking lots and street parking. | 1 |
| Nanning | | | 2017.10 | Half-price parking in designated parking spaces. | 2 |
| Xiangyang | | | 2017.10 | 2-hour/day free parking and half-price parking for the next 2 hours. | 3 |

Note: Elements in *Extra Subsidy*, *Taxi Subsidy*, and *Free Parking* indicate when the corresponding incentives started being implemented, based on published policy documents; the cell is left blank if the incentive did not exist in that particular city.

Table 17: Cities with Extra Incentives

## A.4 Results for $ln(Num/Pop)$ as the Dependent Variable

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.105 | 0.0514 | 0.375*** | 0.214*** | 0.170*** | 0.629*** |
| | (0.064) | (0.086) | (0.099) | (0.081) | (0.062) | (0.144) |
| GDP per Capita | -0.00245 | -0.00333 | -0.00168 | -0.00112 | 0.000501 | 0.00403 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) |
| Pop Density | -1.123 | -0.829 | -0.452 | -0.816 | -0.836 | -0.675 |
| | (0.762) | (0.802) | (0.742) | (0.730) | (0.746) | (0.829) |
| Charging Pts | -0.00742 | -0.00423 | -0.0111 | -0.00846 | -0.00296 | -0.0152 |
| | (0.010) | (0.010) | (0.009) | (0.010) | (0.010) | (0.010) |
| Gas/Electricity | -0.106 | -0.101 | -0.0856 | -0.102 | -0.107 | -0.0961 |
| | (0.066) | (0.066) | (0.064) | (0.067) | (0.065) | (0.065) |
| Edu Exp R | 2.252 | 2.783 | 8.961* | 1.135 | 2.718 | 6.483 |
| | (4.096) | (4.144) | (4.748) | (4.190) | (4.253) | (5.041) |
| Env Exp R | 8.362 | 8.218 | 8.077 | 20.64 | 8.784 | 19.78* |
| | (10.589) | (10.215) | (9.246) | (12.687) | (9.182) | (11.454) |
| License Restriction | 1.099*** | 1.096*** | 1.161*** | 1.130*** | 1.022*** | 1.113*** |
| | (0.124) | (0.123) | (0.120) | (0.130) | (0.151) | (0.155) |
| Driving Restriction | 0.295* | 0.297* | 0.346** | 0.256* | 0.365** | 0.363** |
| | (0.150) | (0.152) | (0.146) | (0.153) | (0.146) | (0.153) |
| Subsidy × GDP per Capita | | 0.000546 | | | | -0.00127* |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.594*** | | | -1.445** |
| | | | (0.481) | | | (0.558) |
| Subsidy × Env Exp R | | | | -4.005 | | -3.591 |
| | | | | (2.746) | | (2.446) |
| Tier=2 × Subsidy | | | | | -0.128*** | -0.116** |
| | | | | | (0.046) | (0.050) |
| Tier=3 × Subsidy | | | | | -0.0992** | -0.0865 |
| | | | | | (0.040) | (0.053) |
| Tier=4 × Subsidy | | | | | -0.155*** | -0.135* |
| | | | | | (0.059) | (0.077) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Baseline and Heterogeneous Effects for $ln(Num/Pop)$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.104 | 0.0635 | 0.372*** | 0.221*** | 0.168*** | 0.669*** |
| | (0.064) | (0.086) | (0.099) | (0.081) | (0.062) | (0.144) |
| GDP per Capita | -0.00219 | -0.00287 | -0.00143 | -0.000739 | 0.000521 | 0.00467 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) |
| Pop Density | -1.497* | -1.248 | -0.818 | -1.221 | -1.192 | -1.200 |
| | (0.800) | (0.845) | (0.783) | (0.767) | (0.800) | (0.855) |
| Charging Pts | -0.00803 | -0.00561 | -0.0117 | -0.00918 | -0.00373 | -0.0173* |
| | (0.010) | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) |
| Gas/Electricity | -0.107 | -0.103 | -0.0865 | -0.102 | -0.107 | -0.0964 |
| | (0.066) | (0.065) | (0.064) | (0.066) | (0.065) | (0.064) |
| Edu Exp R | 2.312 | 2.709 | 8.959* | 1.128 | 2.722 | 6.501 |
| | (4.100) | (4.142) | (4.731) | (4.196) | (4.254) | (5.014) |
| Env Exp R | 9.650 | 9.501 | 9.390 | 22.89* | 9.884 | 22.54** |
| | (10.173) | (9.936) | (8.947) | (12.025) | (8.990) | (11.081) |
| License Lottery (lag) | 1.406*** | 1.391*** | 1.468*** | 1.449*** | 1.278*** | 1.438*** |
| | (0.269) | (0.276) | (0.282) | (0.275) | (0.253) | (0.258) |
| License Auction (lag) | 0.0188*** | 0.0174** | 0.0181*** | 0.0215*** | 0.0168** | 0.0237*** |
| | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) | (0.006) |
| Driving Restriction | 0.263* | 0.265* | 0.313** | 0.217 | 0.331** | 0.318** |
| | (0.147) | (0.149) | (0.145) | (0.150) | (0.143) | (0.151) |
| Subsidy × GDP per Capita | | 0.000415 | | | | -0.00146** |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.581*** | | | -1.511*** |
| | | | (0.479) | | | (0.557) |
| Subsidy × Env Exp R | | | | -4.293 | | -4.033 |
| | | | | (2.780) | | (2.503) |
| Tier=2 × Subsidy | | | | | -0.127*** | -0.117** |
| | | | | | (0.046) | (0.050) |
| Tier=3 × Subsidy | | | | | -0.0936** | -0.0828 |
| | | | | | (0.040) | (0.053) |
| Tier=4 × Subsidy | | | | | -0.147** | -0.130* |
| | | | | | (0.058) | (0.077) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses

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

Table 19: Baseline and Heterogeneous Effects, with *License Lottery* and *License Auction*

## A.5 Baseline and Heterogeneous Effects for $ln(EV\ share)$, using moving average of previous four months for ***License Quotas*** Data

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.106* | 0.0485 | 0.372*** | 0.251*** | 0.171*** | 0.667*** |
| | (0.064) | (0.085) | (0.097) | (0.079) | (0.061) | (0.143) |
| GDP per Capita | -0.00284 | -0.00383 | -0.00210 | -0.00102 | 0.000394 | 0.00449 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Pop Density | -1.787** | -1.414 | -1.105 | -1.484* | -1.432* | -1.427 |
| | (0.866) | (0.899) | (0.845) | (0.831) | (0.828) | (0.864) |
| Charging Pts | -0.0101 | -0.00659 | -0.0136 | -0.0115 | -0.00556 | -0.0186* |
| | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) |
| Gas/Electricity | -0.0928 | -0.0876 | -0.0728 | -0.0864 | -0.0941 | -0.0820 |
| | (0.061) | (0.061) | (0.059) | (0.062) | (0.061) | (0.060) |
| Edu Exp R | 1.257 | 1.826 | 7.848* | -0.214 | 1.783 | 4.938 |
| | (4.104) | (4.112) | (4.658) | (4.134) | (4.215) | (4.915) |
| Env Exp R | 8.103 | 7.892 | 7.833 | 24.50* | 8.598 | 23.97** |
| | (10.462) | (10.085) | (9.211) | (12.482) | (9.140) | (11.392) |
| License Lottery (4-month lags) | 1.879*** | 1.859*** | 1.974*** | 1.930*** | 1.753*** | 1.933*** |
| | (0.158) | (0.162) | (0.154) | (0.168) | (0.202) | (0.214) |
| License Auction (4-month lags) | 0.0207** | 0.0185* | 0.0198** | 0.0248** | 0.0194* | 0.0276*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.009) |
| Driving Restriction | 0.225 | 0.228 | 0.274* | 0.167 | 0.305** | 0.275* |
| | (0.150) | (0.152) | (0.148) | (0.154) | (0.145) | (0.156) |
| Subsidy × GDP per Capita | | 0.000591 | | | | -0.00133** |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.567*** | | | -1.411** |
| | | | (0.467) | | | (0.556) |
| Subsidy × Env Exp R | | | | -5.313** | | -4.946** |
| | | | | (2.606) | | (2.361) |
| Tier=2 × Subsidy | | | | | -0.121*** | -0.109** |
| | | | | | (0.044) | (0.050) |
| Tier=3 × Subsidy | | | | | -0.106*** | -0.0921* |
| | | | | | (0.040) | (0.054) |
| Tier=4 × Subsidy | | | | | -0.160*** | -0.135* |
| | | | | | (0.055) | (0.076) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Baseline and Heterogeneous Effects for $ln(EV\,share)$, with moving average of *License Lottery* and *License Auction* in previous four months

## A.6 Results for $ln(EV\ share)$ with Lagged Number of Charging Facilities

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.0904 | 0.00221 | 0.376*** | 0.219*** | 0.156** | 0.590*** |
| | (0.068) | (0.087) | (0.096) | (0.079) | (0.067) | (0.145) |
| GDP per Capita | -0.000720 | -0.00194 | 0.000213 | 0.000812 | 0.00291 | 0.00559 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Pop Density | -1.327* | -0.851 | -0.608 | -0.960 | -0.988 | -0.675 |
| | (0.780) | (0.808) | (0.748) | (0.739) | (0.726) | (0.812) |
| L.Charging Pts | -0.00695 | -0.00161 | -0.0110 | -0.00823 | -0.00172 | -0.0131 |
| | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) |
| Gas/Electricity | -0.0881 | -0.0784 | -0.0627 | -0.0797 | -0.0878 | -0.0704 |
| | (0.061) | (0.060) | (0.058) | (0.061) | (0.060) | (0.059) |
| Edu Exp R | -0.456 | 0.396 | 6.558 | -1.938 | 0.209 | 3.542 |
| | (4.060) | (4.076) | (4.518) | (4.084) | (4.180) | (4.745) |
| Env Exp R | 6.977 | 6.803 | 6.249 | 21.00 | 7.596 | 19.39* |
| | (10.960) | (10.275) | (9.322) | (13.105) | (9.158) | (11.223) |
| License Restriction | 1.232*** | 1.228*** | 1.300*** | 1.273*** | 1.167*** | 1.263*** |
| | (0.116) | (0.116) | (0.111) | (0.121) | (0.138) | (0.143) |
| Driving Restriction | 0.254* | 0.253* | 0.307** | 0.201 | 0.337** | 0.317** |
| | (0.140) | (0.143) | (0.137) | (0.145) | (0.136) | (0.144) |
| Subsidy × GDP per Capita | | 0.000869* | | | | -0.000964 |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.695*** | | | -1.392*** |
| | | | (0.435) | | | (0.519) |
| Subsidy × Env Exp R | | | | -4.728* | | -4.171* |
| | | | | (2.404) | | (2.106) |
| Tier=2 × Subsidy | | | | | -0.131*** | -0.112** |
| | | | | | (0.043) | (0.049) |
| Tier=3 × Subsidy | | | | | -0.116*** | -0.0922* |
| | | | | | (0.041) | (0.055) |
| Tier=4 × Subsidy | | | | | -0.179*** | -0.143* |
| | | | | | (0.057) | (0.076) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3514 | 3514 | 3514 | 3514 | 3514 | 3514 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Baseline and Heterogeneous Effects for $ln(EV\ share)$ with Lagged Number of Charging Facilities

## A.7 Average Marginal Effects

- Over slopes for different GDPs per capita

```
/*** Average Marginal Effects over Slope of GDP per capita ***/

xtreg lgPt Sub_update GDP_1000 den ChrgPt_1000 Gas_Elec LicR EduExpR_city ///
DR_di EnvExpR c.Sub_update#c.GDP_1000 c.Sub_update#c.EduExpR_city ///
c.Sub_update#c.EnvExpR c.Sub_update#Tier i.T, fe vce(cluster CityID)

margins, dydx(Sub_update) at(GDP_1000=(30(10)170)) vsquish

/* Results:
Average marginal effects                              Number of obs = 3,605
Model VCE: Robust

Expression: Linear prediction, predict()
dy/dx wrt:  Sub_update
1._at:  GDP_1000 =  30
2._at:  GDP_1000 =  40
3._at:  GDP_1000 =  50
4._at:  GDP_1000 =  60
5._at:  GDP_1000 =  70
6._at:  GDP_1000 =  80
7._at:  GDP_1000 =  90
8._at:  GDP_1000 = 100
9._at:  GDP_1000 = 110
10._at: GDP_1000 = 120
11._at: GDP_1000 = 130
12._at: GDP_1000 = 140
13._at: GDP_1000 = 150
14._at: GDP_1000 = 160
15._at: GDP_1000 = 170

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Sub_update   |
         _at |
          1  |   .1279698   .0745656     1.72   0.086    -.0181762    .2741157
          2  |   .1163433   .0713972     1.63   0.103    -.0235925    .2562792
          3  |   .1047169   .0686918     1.52   0.127    -.0299165    .2393504
          4  |   .0930905   .0665061     1.40   0.162    -.0372591      .22344
          5  |   .0814641   .0648926     1.26   0.209     -.045723    .2086511
          6  |   .0698376   .0638946     1.09   0.274    -.0553934    .1950687
          7  |   .0582112   .0635411     0.92   0.360    -.0663271    .1827495
          8  |   .0465848   .0638429     0.73   0.466     -.078545    .1717146
          9  |   .0349584   .0647908     0.54   0.590    -.0920293     .161946
         10  |   .0233319   .0663571     0.35   0.725    -.1067257    .1533895
         11  |   .0117055   .0684995     0.17   0.864     -.122551     .145962
         12  |   .0000791   .0711658     0.00   0.999    -.1394033    .1395615
         13  |  -.0115474   .0742997    -0.16   0.876    -.1571722    .1340775
         14  |  -.0231738   .0778448    -0.30   0.766    -.1757469    .1293993
         15  |  -.0348002   .0817476    -0.43   0.670    -.1950226    .1254222
------------------------------------------------------------------------------
*/
```

- Over slopes for different shares of government expenditure allocated to education

```
/*** Average Marginal Effects over Slope of Edu Exp R ***/

xtreg lgN_Pop Sub_update GDP_1000 den ChrgPt_1000 Gas_Elec LicR EduExpR_city ///
DR_di EnvExpR c.Sub_update#c.GDP_1000 c.Sub_update#c.EduExpR_city ///
c.Sub_update#c.EnvExpR c.Sub_update#Tier i.T, fe vce(cluster CityID)
```

```
margins, dydx(Sub_update) at(EduExpR_city =(0.1(0.01)0.25)) vsquish

/* Results:
Average marginal effects                              Number of obs = 3,605
Model VCE: Robust

Expression: Linear prediction, predict()
dy/dx wrt:  Sub_update
1._at:   EduExpR_city =  .1
2._at:   EduExpR_city = .11
3._at:   EduExpR_city = .12
4._at:   EduExpR_city = .13
5._at:   EduExpR_city = .14
6._at:   EduExpR_city = .15
7._at:   EduExpR_city = .16
8._at:   EduExpR_city = .17
9._at:   EduExpR_city = .18
10._at:  EduExpR_city = .19
11._at:  EduExpR_city =  .2
12._at:  EduExpR_city = .21
13._at:  EduExpR_city = .22
14._at:  EduExpR_city = .23
15._at:  EduExpR_city = .24
16._at:  EduExpR_city = .25

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Sub_update   |
         _at |
          1  |    .169674   .0760004     2.23   0.026     .0207159    .3186321
          2  |   .1561512   .0731355     2.14   0.033     .0128081    .2994942
          3  |   .1426284    .070589     2.02   0.043     .0042765    .2809802
          4  |   .1291055   .0683963     1.89   0.059    -.0049487    .2631597
          5  |   .1155827   .0665924     1.74   0.083     -.014936    .2461014
          6  |   .1020599   .0652096     1.57   0.118    -.0257486    .2298683
          7  |    .088537   .0642751     1.38   0.168    -.0374398    .2145139
          8  |   .0750142   .0638086     1.18   0.240    -.0500483    .2000767
          9  |   .0614914   .0638203     0.96   0.335    -.0635941    .1865768
         10  |   .0479686     .06431     0.75   0.456    -.0780767    .1740138
         11  |   .0344457   .0652669     0.53   0.598    -.0934751    .1623665
         12  |   .0209229    .066671     0.31   0.754    -.1097498    .1515956
         13  |   .0074001   .0684946     0.11   0.914    -.1268469    .1416471
         14  |  -.0061228   .0707055    -0.09   0.931    -.1447029    .1324574
         15  |  -.0196456   .0732684    -0.27   0.789     -.163249    .1239578
         16  |  -.0331684   .0761479    -0.44   0.663    -.1824156    .1160788
------------------------------------------------------------------------------
*/
```

- Over slopes for different shares of government expenditure allocated to environmental protection

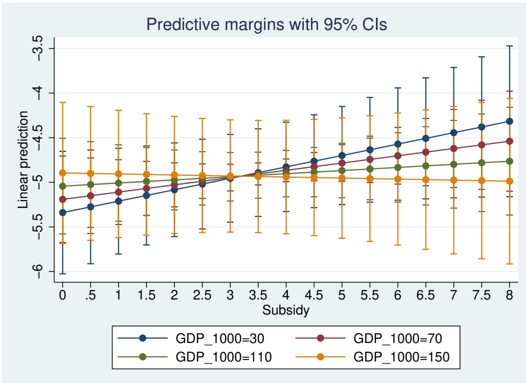
```
/*** Average Marginal Effects over Slope of Env Exp R ***/

xtreg lgPt Sub_update GDP_1000 den ChrgPt_1000 Gas_Elec LicR EduExpR_city ///
DR_di EnvExpR c.Sub_update#c.GDP_1000 c.Sub_update#c.EduExpR_city ///
c.Sub_update#c.EnvExpR c.Sub_update#Tier i.T, fe vce(cluster CityID)

margins, dydx(Sub_update) at(EnvExpR =(0.015(0.005)0.065)) vsquish

/*Result:
Average marginal effects                              Number of obs = 3,605
Model VCE: Robust

Expression: Linear prediction, predict()
dy/dx wrt:  Sub_update
```

```
1._at:  EnvExpR = .015
2._at:  EnvExpR =  .02
3._at:  EnvExpR = .025
4._at:  EnvExpR =  .03
5._at:  EnvExpR = .035
6._at:  EnvExpR =  .04
7._at:  EnvExpR = .045
8._at:  EnvExpR =  .05
9._at:  EnvExpR = .055
10._at: EnvExpR =  .06
11._at: EnvExpR = .065

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Sub_update   |
         _at |
          1  |   .1459686   .0614951     2.37   0.018     .0254406    .2664967
          2  |   .1230132   .0594858     2.07   0.039     .0064232    .2396032
          3  |   .1000578   .0596934     1.68   0.094    -.0169391    .2170546
          4  |   .0771023   .0620956     1.24   0.214    -.0446028    .1988074
          5  |   .0541469   .0664548     0.81   0.415    -.0761022    .1843959
          6  |   .0311914   .0724186     0.43   0.667    -.1107463    .1731292
          7  |    .008236   .0796271     0.10   0.918    -.1478302    .1643022
          8  |  -.0147195   .0877742    -0.17   0.867    -.1867538    .1573149
          9  |  -.0376749   .0966229    -0.39   0.697    -.2270523    .1517025
         10  |  -.0606304   .1059975    -0.57   0.567    -.2683816    .1471209
         11  |  -.0835858   .1157704    -0.72   0.470    -.3104916      .14332
------------------------------------------------------------------------------
*/
```

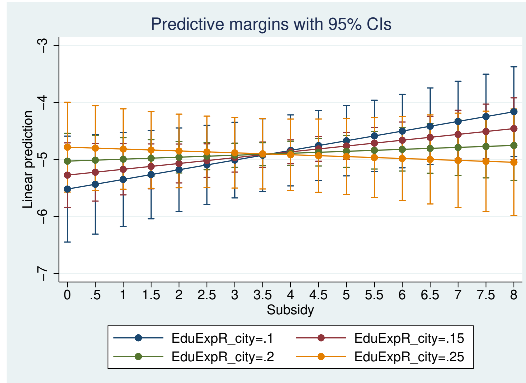
- Over slopes for different city tiers

```
/*** Average Marginal Effects over Slopes of Different Tiers ***/

xtreg lgPt Sub_update GDP_1000 den ChrgPt_1000 Gas_Elec LicR EduExpR_city ///
DR_di EnvExpR c.Sub_update#c.GDP_1000 c.Sub_update#c.EduExpR_city ///
c.Sub_update#c.EnvExpR c.Sub_update#Tier i.T, fe vce(cluster CityID)

margins, dydx(Sub_update) at(Tier=(1(1)4)) vsquish

/* Results:
Average marginal effects                                 Number of obs = 3,605
Model VCE: Robust

Expression: Linear prediction, predict()
dy/dx wrt:  Sub_update
1._at: Tier = 1
2._at: Tier = 2
3._at: Tier = 3
4._at: Tier = 4

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Sub_update   |
         _at |
          1  |   .1508307   .0714038     2.11   0.035     .0108818    .2907797
          2  |   .0430152   .0747858     0.58   0.565    -.1035623    .1895927
          3  |   .0564669   .0630704     0.90   0.371    -.0671488    .1800826
          4  |   .0137369   .0860504     0.16   0.873    -.1549187    .1823926
------------------------------------------------------------------------------
*/
```

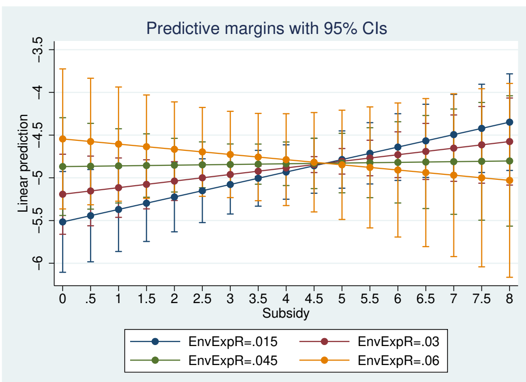
- Graphs for Predicted Values



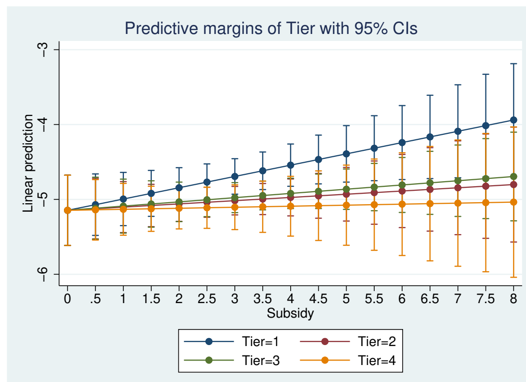

(a) GPD Per Capita




(b) Edu Exp R




(c) Env Exp R




(b) Tier

Figure 10: Predicted Values for Subsidies when Including Interactions

## A.8 Regression Results for $ln(Num/Pop)$ with Extra Incentives

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.0863 | 0.0471 | 0.332*** | 0.229** | 0.145** | 0.620*** |
| | (0.065) | (0.086) | (0.102) | (0.098) | (0.065) | (0.145) |
| GDP per Capita | -0.00275 | -0.00347 | -0.00204 | -0.00142 | -0.000438 | 0.00319 |
| | (0.005) | (0.005) | (0.005) | (0.006) | (0.005) | (0.005) |
| Pop Density | -1.576* | -1.337 | -0.958 | -1.297* | -1.327 | -1.257 |
| | (0.806) | (0.848) | (0.798) | (0.769) | (0.810) | (0.850) |
| Charging Pts | -0.00749 | -0.00514 | -0.0109 | -0.00897 | -0.00340 | -0.0158 |
| | (0.010) | (0.010) | (0.009) | (0.010) | (0.009) | (0.011) |
| Gas/Electricity | -0.107 | -0.104 | -0.0896 | -0.106 | -0.106* | -0.0980 |
| | (0.065) | (0.065) | (0.063) | (0.065) | (0.064) | (0.063) |
| Edu Exp R | 2.738 | 3.143 | 8.729* | 1.460 | 3.094 | 6.339 |
| | (4.080) | (4.136) | (4.734) | (4.154) | (4.227) | (4.978) |
| Env Exp R | 10.35 | 10.22 | 10.05 | 26.50* | 10.42 | 24.96** |
| | (10.325) | (10.089) | (9.169) | (13.736) | (9.163) | (12.541) |
| License Lottery (lag) | 1.407*** | 1.391*** | 1.461*** | 1.452*** | 1.279*** | 1.429*** |
| | (0.258) | (0.263) | (0.269) | (0.257) | (0.239) | (0.240) |
| License Auction (lag) | 0.0196*** | 0.0183** | 0.0189*** | 0.0233*** | 0.0179** | 0.0249*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| Driving Restriction | 0.264* | 0.265* | 0.308** | 0.200 | 0.320** | 0.290* |
| | (0.146) | (0.147) | (0.145) | (0.153) | (0.142) | (0.158) |
| Extra Subsidy | 0.941*** | 0.924*** | 0.803*** | 0.866*** | 0.892*** | 0.755** |
| | (0.256) | (0.263) | (0.284) | (0.306) | (0.309) | (0.349) |
| Taxi Subsidy | 0.00414 | 0.0421 | 0.0455 | 0.308 | -0.000688 | 0.191 |
| | (0.182) | (0.191) | (0.203) | (0.290) | (0.201) | (0.288) |
| Free Parking | 0.282 | 0.291 | 0.272 | 0.323 | 0.222 | 0.231 |
| | (0.291) | (0.284) | (0.308) | (0.239) | (0.397) | (0.375) |
| Subsidy × GDP per Capita | | 0.000406 | | | | -0.00124* |
| | | (0.000) | | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.432*** | | | -1.370** |
| | | | (0.491) | | | (0.564) |
| Subsidy × Env Exp R | | | | -5.176 | | -4.651 |
| | | | | (3.314) | | (2.959) |
| Tier=2 × Subsidy | | | | | -0.122*** | -0.108** |
| | | | | | (0.046) | (0.051) |
| Tier=3 × Subsidy | | | | | -0.0795* | -0.0665 |
| | | | | | (0.041) | (0.055) |
| Tier=4 × Subsidy | | | | | -0.136** | -0.113 |
| | | | | | (0.058) | (0.078) |
| City FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses

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

Table 22: Results for $ln(Num/Pop)$ with Extra Incentives

## A.9 Regression Results for $ln(BEV/Pop)$ as the Dependent Variable

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Subsidy (BEV) | 0.0765 | 0.0575 | 0.0133 | 0.379*** | 0.163* | 0.117* | 0.546*** | 0.495*** |
| | (0.064) | (0.066) | (0.091) | (0.098) | (0.087) | (0.066) | (0.169) | (0.168) |
| GDP per Capita | 0.00675 | 0.00596 | 0.00628 | 0.00902 | 0.00770 | 0.00916 | 0.0114* | 0.00979 |
| | (0.007) | (0.007) | (0.007) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) |
| Edu Exp R | 5.378 | 5.854 | 5.855 | 13.04*** | 4.468 | 5.748 | 11.79** | 11.55** |
| | (4.083) | (4.049) | (4.128) | (4.598) | (4.153) | (4.239) | (4.853) | (4.819) |
| Env Exp R | 17.53 | 18.24 | 17.60 | 17.45* | 28.39** | 17.81* | 27.25** | 29.80** |
| | (10.965) | (11.041) | (10.585) | (9.557) | (13.388) | (10.197) | (12.192) | (13.877) |
| License Lottery (lag) | 1.338*** | 1.345*** | 1.314*** | 1.403*** | 1.372*** | 1.268*** | 1.409*** | 1.403*** |
| | (0.305) | (0.298) | (0.314) | (0.323) | (0.309) | (0.327) | (0.330) | (0.312) |
| License Auction (lag) | 0.0212*** | 0.0219*** | 0.0189** | 0.0205*** | 0.0233*** | 0.0193** | 0.0244*** | 0.0255*** |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) |
| Driving Restriction | 0.353** | 0.351** | 0.357** | 0.406*** | 0.318** | 0.413*** | 0.393** | 0.363** |
| | (0.148) | (0.155) | (0.150) | (0.150) | (0.153) | (0.154) | (0.163) | (0.171) |
| Extra Subsidy | | 0.996*** | | | | | | 0.793** |
| | | (0.314) | | | | | | (0.382) |
| Taxi Subsidy | | -0.0339 | | | | | | 0.174 |
| | | (0.179) | | | | | | (0.305) |
| Free Parking | | 0.0540 | | | | | | 0.0435 |
| | | (0.539) | | | | | | (0.557) |
| Subsidy (BEV) × GDP per Capita | | | 0.000664 | | | | -0.000752 | -0.000547 |
| | | | (0.001) | | | | (0.001) | (0.001) |
| Subsidy (BEV) × Edu Exp R | | | | -1.744*** | | | -1.729*** | -1.578*** |
| | | | | (0.457) | | | (0.539) | (0.543) |
| Subsidy (BEV) × Env Exp R | | | | | -3.216 | | -2.914 | -3.497 |
| | | | | | (2.806) | | (2.471) | (3.007) |
| Tier=2 × Subsidy (BEV) | | | | | | -0.0793 | -0.0479 | -0.0412 |
| | | | | | | (0.049) | (0.051) | (0.053) |
| Tier=3 × Subsidy (BEV) | | | | | | -0.0678 | -0.0268 | -0.0125 |
| | | | | | | (0.043) | (0.060) | (0.062) |
| Tier=4 × Subsidy (BEV) | | | | | | -0.117** | -0.0624 | -0.0467 |
| | | | | | | (0.059) | (0.081) | (0.085) |
| Other Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3450 | 3450 | 3450 | 3450 | 3450 | 3450 | 3450 | 3450 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Results for $ln(BEV/Pop)$

## A.10 Regressions with Lagged Dependent Variables using Arellano-Bond estimator

One may worry that including lagged dependent variable terms violates the strict exogeneity, therefore a generalized method of moments estimator introduced by Arellano and Bond (1991) is used to estimate the fixed effects in equation (6). Since the Arellano-Bond estimator is designed for situations with "small T, large N" panels,[65] regression results using quarterly-level data are shown and should be considered more accurate than the ones based on monthly-level data. However, given that this study has a relatively small $N$, the cluster–robust standard errors and the Arellano–Bond autocorrelation test may be unreliable (Roodman, 2009).

Regression results in Table 24 are estimated using a generalized method of moments estimator (GMM) proposed by Arellano and Bond (1991). The p-values of Hansen statistic for the overidentifying restrictions test are presented in the table, which verify that the model is not overspecified.

[65] "Small T, large N" refers to few time periods and many individuals (cities).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| L.ln(EV share) | 0.300*** | 0.311*** | 0.191*** | 0.225*** | 0.155** | 0.189*** |
| | (0.056) | (0.053) | (0.065) | (0.056) | (0.064) | (0.061) |
| L2.ln(EV share) | | 0.164*** | | 0.136*** | | 0.108** |
| | | (0.039) | | (0.044) | | (0.048) |
| Subsidy | 0.130* | 0.144* | 0.575** | 0.419** | 2.305** | 1.971** |
| | (0.074) | (0.084) | (0.236) | (0.167) | (0.995) | (0.858) |
| License Lottery (lag) | 0.316 | 0.273 | -0.226 | -0.0933 | 0.544 | 0.619 |
| | (0.555) | (0.679) | (0.809) | (0.722) | (0.648) | (0.622) |
| License Auction (lag) | 0.00612 | 0.0117 | -0.0101 | -0.00554 | -0.00410 | -0.00669 |
| | (0.015) | (0.012) | (0.016) | (0.015) | (0.015) | (0.013) |
| Driving Restriction | 0.536*** | 0.330* | 0.319 | 0.230 | 0.460** | 0.370 |
| | (0.172) | (0.186) | (0.248) | (0.237) | (0.233) | (0.226) |
| Subsidy × GDP per Capita | | | | | -0.00579 | -0.000790 |
| | | | | | (0.005) | (0.005) |
| Subsidy × Edu Exp R | | | | | -6.614 | -9.122* |
| | | | | | (5.984) | (5.196) |
| Subsidy × Env Exp R | | | | | 0.857 | -0.974 |
| | | | | | (16.544) | (13.695) |
| Tier=2 × Subsidy | | | -1.001** | -0.746** | -0.968* | -0.411 |
| | | | (0.434) | (0.317) | (0.563) | (0.492) |
| Tier=3 × Subsidy | | | -0.637* | -0.284 | -0.955 | -0.253 |
| | | | (0.349) | (0.262) | (0.605) | (0.567) |
| Tier=4 × Subsidy | | | -0.347 | -0.427* | -0.820 | -0.382 |
| | | | (0.312) | (0.223) | (0.628) | (0.559) |
| Hansen p-value | 0.211 | 0.749 | 0.409 | 0.804 | 0.383 | 0.678 |
| Instruments | Lags(1-6) of LDV | Lags(1-6) of LDVs | Lags(1-6) of LDV | Lags(1-6) of LDVs | Lags(1-6) of LDV | Lags(1-6) of LDVs |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 1163 | 1065 | 1163 | 1065 | 1163 | 1065 |

Standard errors in parentheses

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

Notes: LDV refers to lagged dependent variable.

Table 24: Arellano-Bond Estimator with the LDVs, Quarterly $ln(EV\ share)$

## A.11 DID Model for the 2017 Treatment

### A.11.1 The Average Total Subsidy

The average total subsidy generally decreased every year except for 2018. The changes in the subsidies for the treatment and the control group differ the most from 2016 to 2017; in the later years, the changes in the subsidies received by these two groups are very similar.

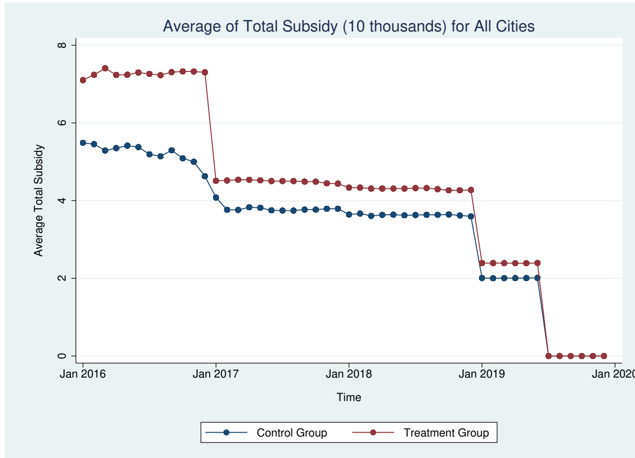



Figure 11: Average Total Subsidy for All Sampled Cities

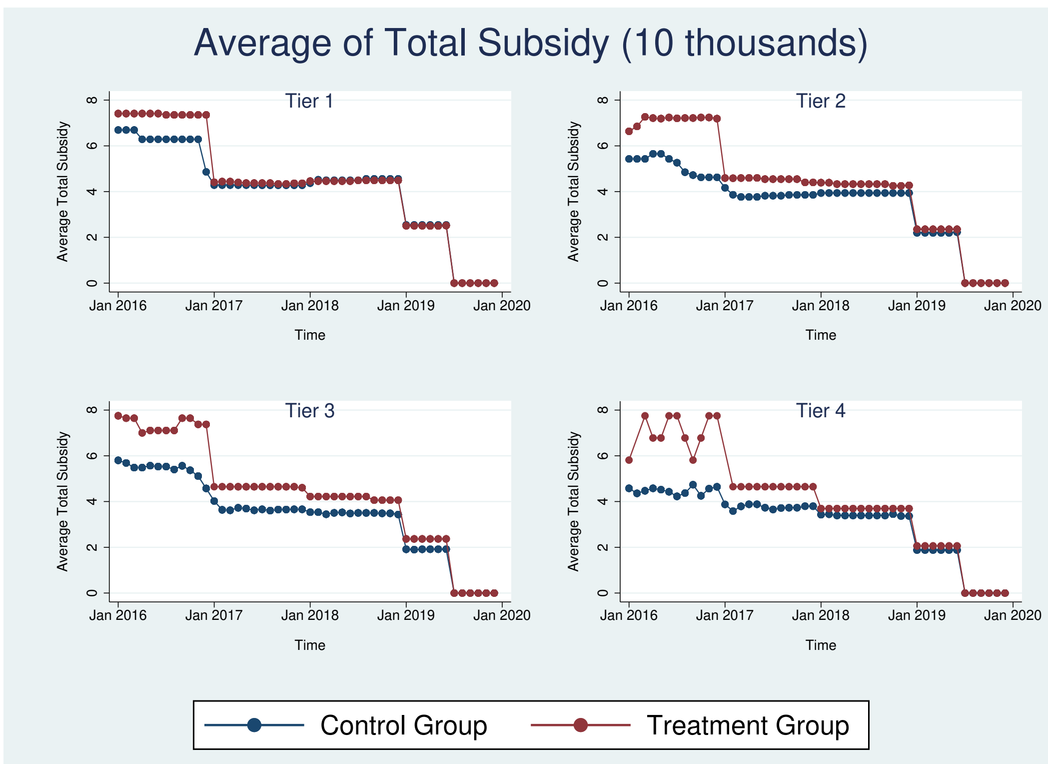
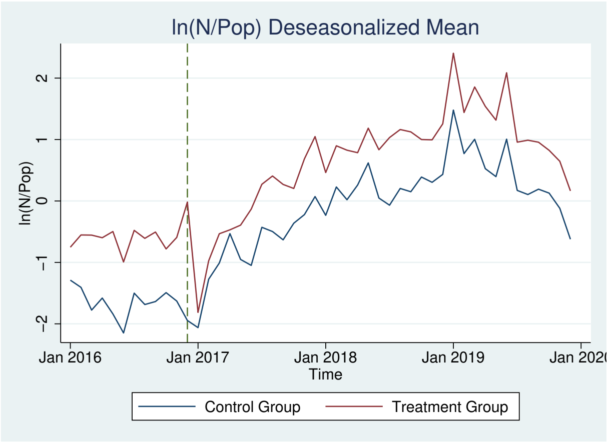


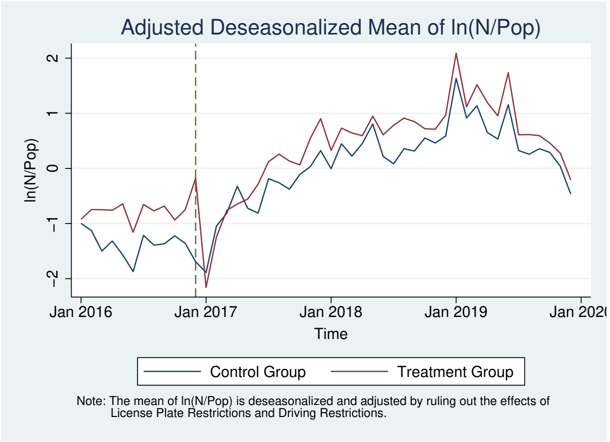

Figure 12: Average Total Subsidy for Different Tiers Across Time

### A.11.2 Graphs for the Monthly Deseasonalized Mean

Figure 13 shows the deseasonalized and adjusted trends for $ln(Num/Pop)$. Figure 14 shows the deseasonalized mean of $ln(Num/Pop)$ for different city tiers.




(a)




(b)

Figure 13: Deseasonalized and Adjusted Mean of $ln(Num/Pop)$

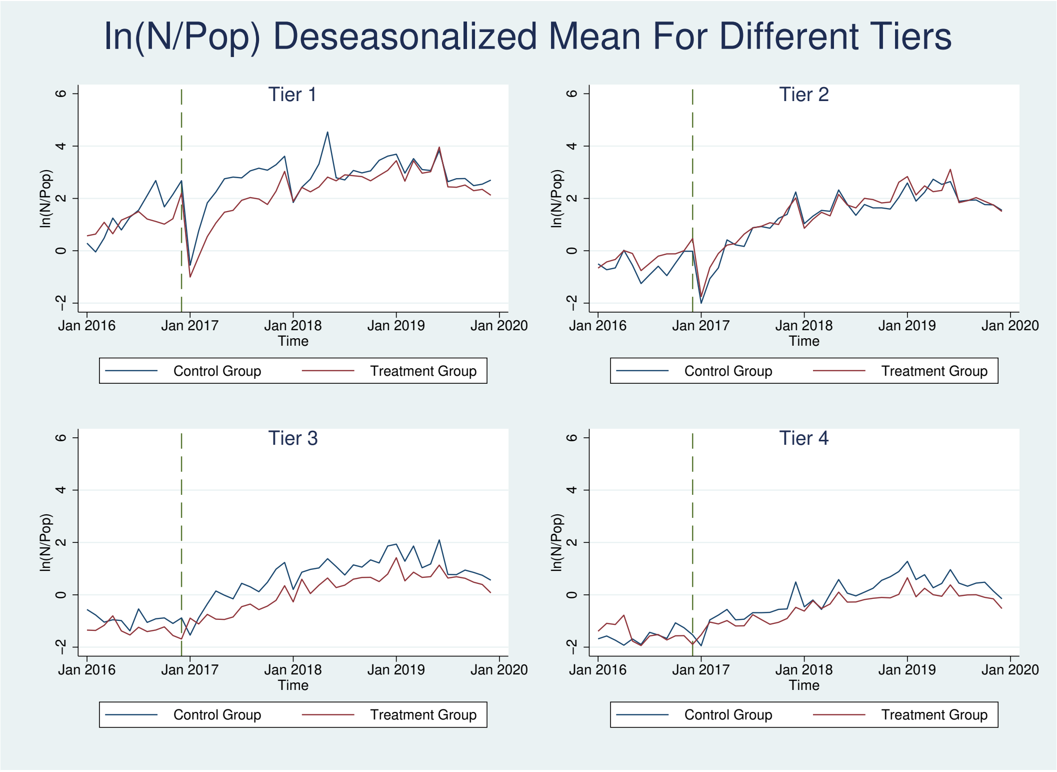
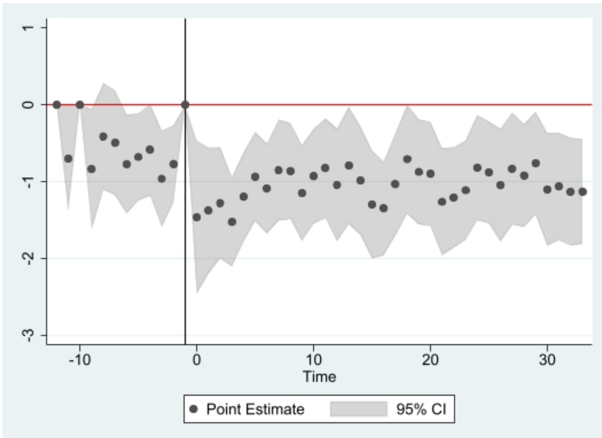


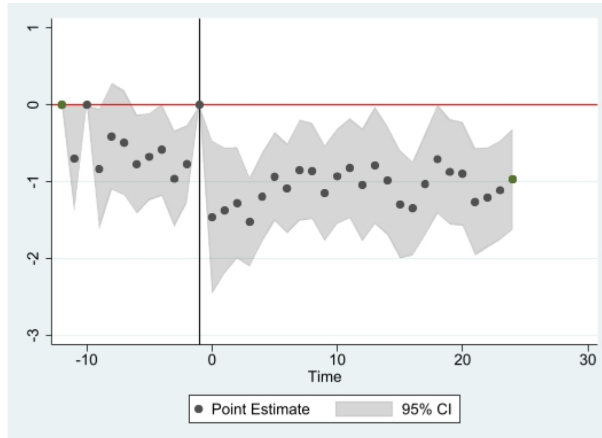

Figure 14: Deseasonalized Trends for Different Tiers, Monthly Data

### A.11.3 Graphs for the Panel Event Study

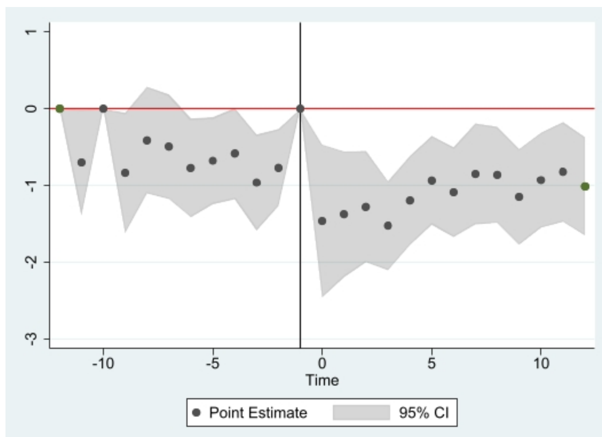
Figure 15 presents the lag and lead coefficients relative to 2017 new policy in the panel event study analyses for different time windows. 95% confidence intervals are used in the plots. A joint significance test for lags in each event study analysis is conducted and the F-statistic indicates that the null hypothesis cannot be rejected at 95% confidence level.[66] The plots and the F-statistics confirm that the lags are jointly indifferent from zero at 95% confidence intervals, which validates the parallel pre-trend assumption for the DID analysis.




(a) Full Sample Periods




(b) From 2016 to 2018



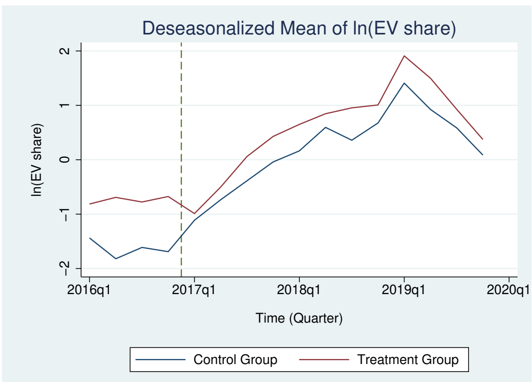

(c) From 2016 to 2017

Figure 15: Lag and Lead Coefficients Plots with 95% Confidence Intervals for $ln(EV\ share)$

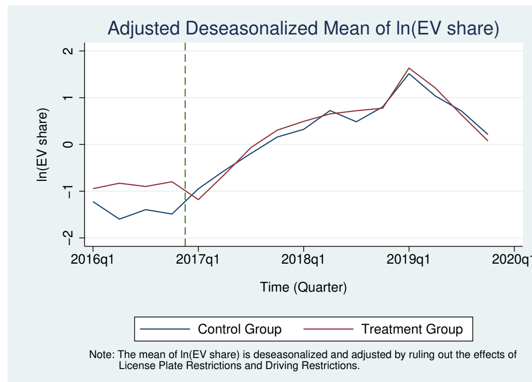
### A.11.4 DID Analysis Using Quarterly Data

To further reduce the fluctuations in the dependent variable, I also aggregate the monthly data to the quarterly level; the deseasonalized trends for quarterly data are shown below. Although only four pre-treatment time periods are available, we can still see that the pre-trends are roughly parallel, and there is a visible decrease between the two lines after the treatment.

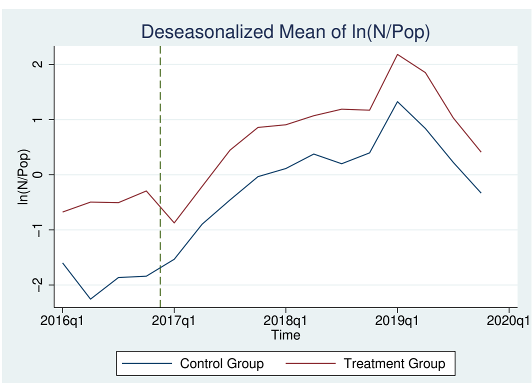
[66] The F-statistics for Figure 15(a), (b), (c) are 1.7918 (p-value: 0.0813), 1.7973 (p-value: 0.0803), 1.8041 (p-value: 0.0790), respectively.



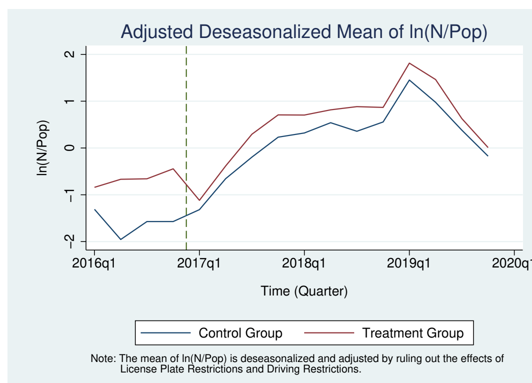

(a) $ln(EV\ share)$, Deseasonalized




(b) $ln(EV\ share)$, Deseasonalized and adjusted




(c) $ln(Num/Pop)$, Deseasonalized




(d) $ln(Num/Pop)$, Deseasonalized and adjusted

Figure 16: Trends, Quarterly Data

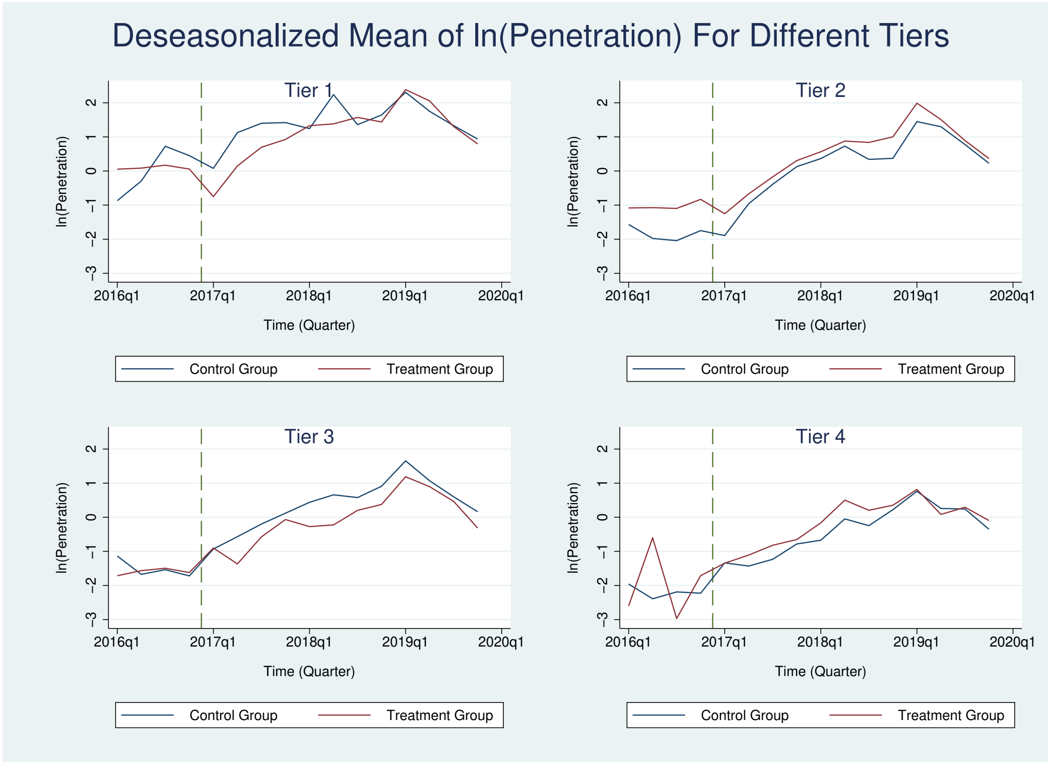



Figure 17: Deseasonalized Trends for Different Tiers, Quarterly $ln(EV\ share)$

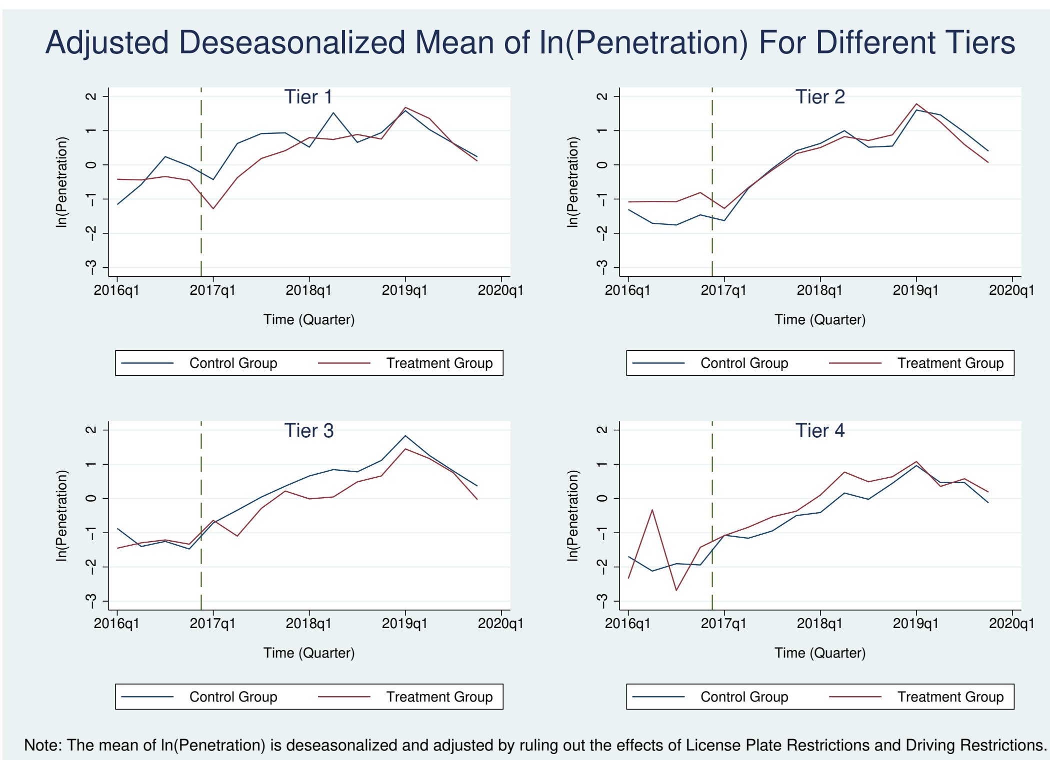



Figure 18: Adjusted Deseasonalized Trends for Different Tiers, Quarterly $ln(EV\ share)$

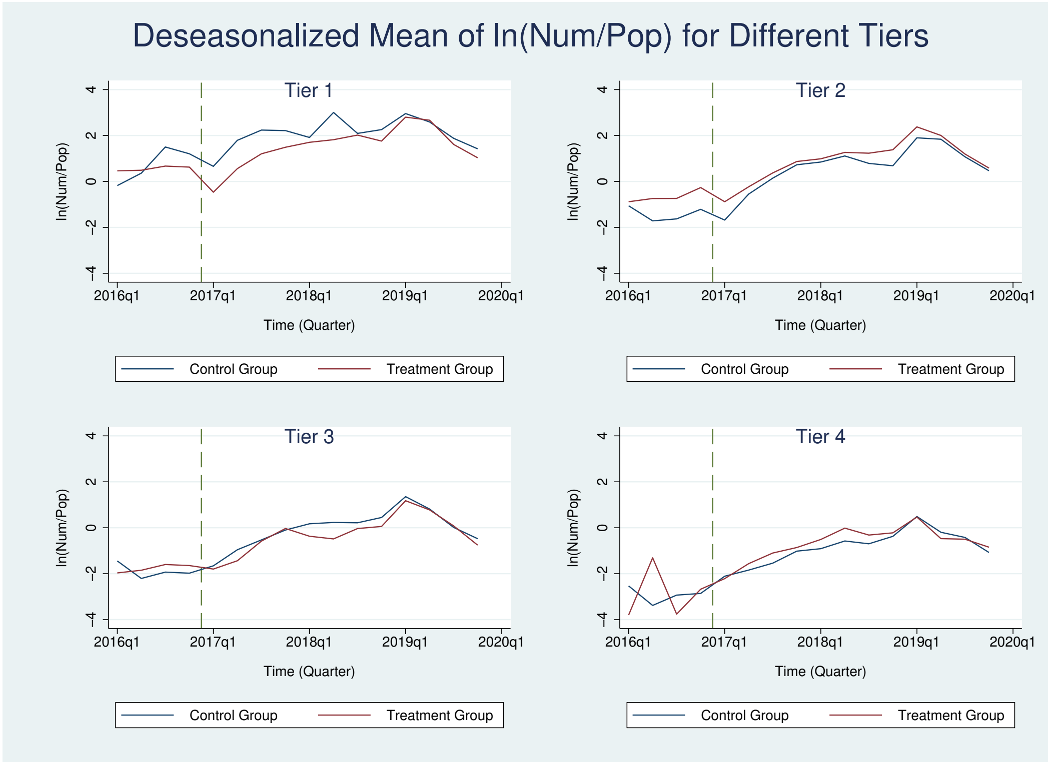



Figure 19: Deseasonalized Trends for Different Tiers, Quarterly ln(Num/Pop)

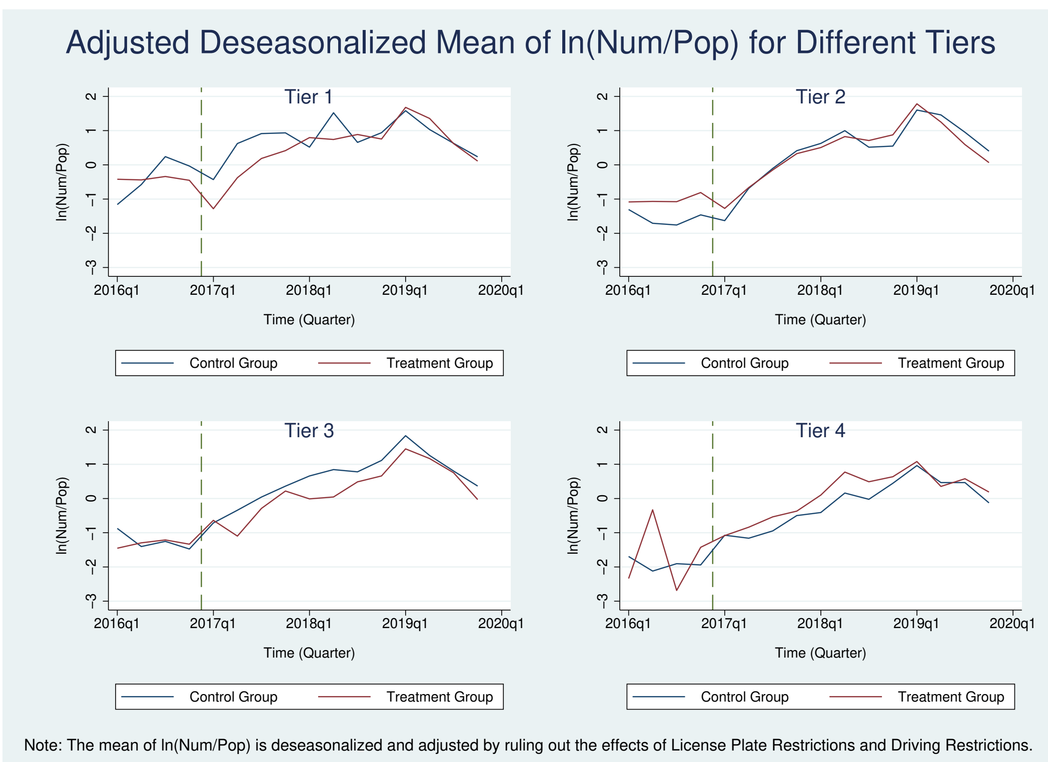



Figure 20: Adjusted Deseasonalized Trends for Different Tiers, Quarterly ln(Num/Pop)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Post17*Treat | -0.519** | -0.575*** | -0.868*** | -0.543*** | -0.550*** | -0.758*** | -0.563*** | -0.568*** | -0.691*** |
| | (0.198) | (0.212) | (0.223) | (0.199) | (0.208) | (0.220) | (0.194) | (0.205) | (0.251) |
| License Lottery (lag) | | 1.595*** | 1.549*** | | 2.211 | 2.213 | | -142.1 | -111.7 |
| | | (0.225) | (0.215) | | (2.908) | (2.658) | | (156.067) | (174.470) |
| License Auction (lag) | | 0.0201** | 0.0227** | | 0.0226** | 0.0244** | | 0.0329** | 0.0311** |
| | | (0.009) | (0.009) | | (0.009) | (0.010) | | (0.015) | (0.015) |
| Driving Restriction | | 0.253 | 0.268* | | 0.431** | 0.444** | | 1.246*** | 1.238*** |
| | | (0.153) | (0.143) | | (0.211) | (0.203) | | (0.258) | (0.260) |
| Tier=2 × Post17*Treat | | | 0.481 | | | 0.381 | | | 0.175 |
| | | | (0.322) | | | (0.310) | | | (0.344) |
| Tier=3 × Post17*Treat | | | 0.490 | | | 0.289 | | | 0.273 |
| | | | (0.407) | | | (0.410) | | | (0.467) |
| Tier=4 × Post17*Treat | | | 0.287 | | | 0.0366 | | | 0.0108 |
| | | | (0.206) | | | (0.206) | | | (0.231) |
| Controls | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample Periods | 2016-2019 | 2016-2019 | 2016-2019 | 2016-2018 | 2016-2018 | 2016-2018 | 2016-2017 | 2016-2017 | 2016-2017 |
| Observations | 1365 | 1269 | 1269 | 1017 | 925 | 925 | 669 | 579 | 579 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: DID Results for $ln(EV\ share)$, Quarterly Data

### A.11.5 Including Five More Cities and Placebo Tests

Table 26 shows the results of the analyses conducted after moving five more cities from the control group to the treatment group. The five cities are: Changsha, Ningbo, Sanming, Weifang, and Zhuzhou, because those five cities changed their local subsidies from above 50% to below 50% one month before 2017.

Table 27 displays the results of the placebo tests. $Post19$ and $Post18$ are dummy variables indicating whether the observation was recorded after January 2019 or January 2018, respectively. The first five columns use the full sample periods from 2016 to 2019, while the last three columns only use data from 2017 to 2018 and are regressed on $Post18$. From the placebo tests results, we can see that the coefficients for $Post19$ and $Post18$ are not significant.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Post17*Treat | -0.345* | -0.403* | -0.649*** | -0.331 | -0.381* | -0.566*** | -0.263 | -0.356* | -0.534** |
| | (0.205) | (0.210) | (0.218) | (0.205) | (0.204) | (0.210) | (0.194) | (0.191) | (0.218) |
| License Lottery (lag) | | 1.522*** | 1.491*** | | 2.663*** | 2.583** | | -11.46 | -7.020 |
| | | (0.305) | (0.305) | | (0.978) | (0.993) | | (38.396) | (42.806) |
| License Auction (lag) | | 0.0157** | 0.0171** | | 0.0168* | 0.0174* | | 0.0136 | 0.0145 |
| | | (0.007) | (0.008) | | (0.009) | (0.010) | | (0.015) | (0.016) |
| Driving Restriction | | 0.256* | 0.293* | | 0.463** | 0.489** | | 1.003** | 1.044** |
| | | (0.147) | (0.148) | | (0.209) | (0.210) | | (0.500) | (0.501) |
| Tier=2 × Post17*Treat | | | 0.307 | | | 0.214 | | | 0.144 |
| | | | (0.299) | | | (0.293) | | | (0.302) |
| Tier=3 × Post17*Treat | | | 0.531* | | | 0.422 | | | 0.516 |
| | | | (0.283) | | | (0.300) | | | (0.321) |
| Tier=4 × Post17*Treat | | | 0.332* | | | 0.124 | | | 0.225 |
| | | | (0.187) | | | (0.186) | | | (0.179) |
| Controls | | ✓ | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample Periods | 2016-2019 | 2016-2019 | 2016-2019 | 2016-2018 | 2016-2018 | 2016-2018 | 2016-2017 | 2016-2017 | 2016-2017 |
| Observations | 3945 | 3605 | 3605 | 2902 | 2746 | 2746 | 1862 | 1706 | 1706 |

Standard errors in parentheses

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

Table 26: DID Results for $ln(EV\ share)$, Including five more cities

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Post19*Treat | 0.000259 | -0.00626 | | | | | | |
| | (0.132) | (0.123) | | | | | | |
| Post18*Treat | | | -0.130 | -0.122 | -0.199 | 0.0488 | 0.0642 | 0.209 |
| | | | (0.162) | (0.162) | (0.195) | (0.138) | (0.153) | (0.183) |
| License Lottery (lag) | | 1.499*** | | 1.524*** | 1.480*** | | 1.011* | 0.667 |
| | | (0.288) | | (0.304) | (0.296) | | (0.553) | (0.625) |
| License Auction (lag) | | 0.0152** | | 0.0154** | 0.0159** | | 0.0125 | 0.0127 |
| | | (0.007) | | (0.007) | (0.007) | | (0.009) | (0.009) |
| Driving Restriction | | 0.245 | | 0.251* | 0.259* | | -0.0695 | -0.121 |
| | | (0.149) | | (0.147) | (0.145) | | (0.108) | (0.119) |
| Tier=2 × Post18*Treat | | | | | 0.162 | | | -0.105 |
| | | | | | (0.225) | | | (0.227) |
| Tier=3 × Post18*Treat | | | | | 0.0574 | | | -0.342 |
| | | | | | (0.261) | | | (0.315) |
| Tier=4 × Post18*Treat | | | | | 0.0856 | | | -0.841*** |
| | | | | | (0.244) | | | (0.253) |
| Controls | | ✓ | | ✓ | ✓ | | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sample Periods | 2016 - 19 | 2016 - 19 | 2016 - 19 | 2016 - 19 | 2016 - 19 | 2017 - 18 | 2017 - 18 | 2017 - 18 |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 1969 | 1969 | 1969 |

Standard errors in parentheses

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

Table 27: Placebo Tests Results for $ln(EV\ share)$

## A.12 Regressions on the Subsidy Dummy for $ln(Num/Pop)$

Table 28 shows the subsidy dummy regression results for $ln(Num/Pop)$, corresponding to Table 12.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Sub Dummy | 0.209 | 0.159 | 0.631*** | 0.476** | 2.470*** | 2.134*** |
| | (0.139) | (0.147) | (0.159) | (0.194) | (0.732) | (0.764) |
| License Lottery (lag) | 1.418*** | 1.416*** | 1.404*** | 1.409*** | 1.499*** | 1.498*** |
| | (0.259) | (0.248) | (0.281) | (0.270) | (0.281) | (0.268) |
| License Auction (lag) | 0.0185** | 0.0194*** | 0.0147** | 0.0166** | 0.0206*** | 0.0217*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) |
| Driving Restriction | 0.241 | 0.246* | 0.256* | 0.256* | 0.223 | 0.217 |
| | (0.145) | (0.142) | (0.139) | (0.138) | (0.147) | (0.148) |
| Extra Subsidy | | 0.924*** | | 0.806** | | 0.810** |
| | | (0.248) | | (0.322) | | (0.362) |
| Taxi Subsidy | | 0.0467 | | 0.00636 | | -0.00193 |
| | | (0.186) | | (0.217) | | (0.245) |
| Free Parking | | 0.302 | | 0.260 | | 0.291 |
| | | (0.299) | | (0.360) | | (0.326) |
| Sub Dummy × GDP per Capita | | | | | -0.00139 | -0.0000816 |
| | | | | | (0.003) | (0.003) |
| Sub Dummy × Edu Exp R | | | | | -7.048** | -6.474* |
| | | | | | (3.389) | (3.433) |
| Sub Dummy × Env Exp R | | | | | -22.27 | -24.26* |
| | | | | | (13.735) | (14.010) |
| Tier=2 × Sub Dummy | | | -0.457** | -0.345 | -0.287 | -0.154 |
| | | | (0.200) | (0.217) | (0.221) | (0.243) |
| Tier=3 × Sub Dummy | | | -0.351 | -0.214 | -0.117 | 0.0656 |
| | | | (0.229) | (0.249) | (0.314) | (0.340) |
| Tier=4 × Sub Dummy | | | -0.858*** | -0.710** | -0.532 | -0.320 |
| | | | (0.267) | (0.284) | (0.388) | (0.416) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3605 | 3605 | 3605 | 3605 | 3605 | 3605 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 28: Subsidy Dummy Results for $ln(Num/Pop)$

## A.13 Regressions on Quarterly Data for $ln(Num/Pop)$

Table 29 shows the regression results for quarterly $ln(Num/Pop)$, corresponding to Table 13.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.153** | 0.219*** | 0.767*** | 0.138* | 0.202*** | 0.734*** |
| | (0.071) | (0.070) | (0.158) | (0.074) | (0.074) | (0.161) |
| License Lottery (lag) | 1.408*** | 1.255*** | 1.480*** | 1.396*** | 1.247*** | 1.465*** |
| | (0.181) | (0.202) | (0.211) | (0.177) | (0.197) | (0.207) |
| License Auction (lag) | 0.0175** | 0.0151* | 0.0236*** | 0.0180** | 0.0160** | 0.0245*** |
| | (0.009) | (0.008) | (0.007) | (0.009) | (0.008) | (0.007) |
| Driving Restriction | 0.173 | 0.252* | 0.241 | 0.183 | 0.250* | 0.226 |
| | (0.163) | (0.151) | (0.157) | (0.162) | (0.150) | (0.163) |
| Extra Subsidy | | | | 0.827*** | 0.751** | 0.629 |
| | | | | (0.296) | (0.363) | (0.410) |
| Taxi Subsidy | | | | -0.0981 | -0.0867 | 0.0777 |
| | | | | (0.238) | (0.253) | (0.321) |
| Free Parking | | | | 0.0974 | 0.0192 | 0.00736 |
| | | | | (0.222) | (0.351) | (0.360) |
| Subsidy × GDP per Capita | | | -0.00170** | | | -0.00157** |
| | | | (0.001) | | | (0.001) |
| Subsidy × Edu Exp R | | | -1.592*** | | | -1.502** |
| | | | (0.579) | | | (0.577) |
| Subsidy × Env Exp R | | | -4.175* | | | -4.521* |
| | | | (2.251) | | | (2.614) |
| Tier=2 × Subsidy | | -0.134*** | -0.129** | | -0.130*** | -0.123** |
| | | (0.046) | (0.050) | | (0.046) | (0.051) |
| Tier=3 × Subsidy | | -0.109** | -0.106* | | -0.0980** | -0.0947* |
| | | (0.043) | (0.055) | | (0.044) | (0.057) |
| Tier=4 × Subsidy | | -0.193*** | -0.187** | | -0.183*** | -0.174** |
| | | (0.063) | (0.080) | | (0.064) | (0.083) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City FE & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 1269 | 1269 | 1269 | 1269 | 1269 | 1269 |

Standard errors in parentheses

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

Table 29: Results for $ln(Num/Pop)$, Quarterly Data

## A.14 Regressions Including the Lags of the Dependent Variable, $ln(Num/Pop)$

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Subsidy | 0.0939** | 0.0823** | 0.420*** | 0.371*** | 0.391*** | 0.344*** |
| | (0.038) | (0.037) | (0.084) | (0.081) | (0.086) | (0.082) |
| 1-Lag of ln(N/Pop) | 0.457*** | 0.412*** | 0.450*** | 0.407*** | 0.446*** | 0.404*** |
| | (0.024) | (0.023) | (0.024) | (0.023) | (0.024) | (0.023) |
| 2-Lag of ln(N/Pop) | | 0.119*** | | 0.115*** | | 0.112*** |
| | | (0.018) | | (0.018) | | (0.018) |
| License Lottery (lag) | 0.804*** | 0.714*** | 0.916*** | 0.815*** | 0.913*** | 0.814*** |
| | (0.156) | (0.121) | (0.162) | (0.125) | (0.152) | (0.116) |
| License Auction (lag) | 0.0115*** | 0.0100*** | 0.0155*** | 0.0134*** | 0.0161*** | 0.0140*** |
| | (0.004) | (0.003) | (0.004) | (0.003) | (0.004) | (0.003) |
| Driving Restriction | 0.155** | 0.115** | 0.154* | 0.107* | 0.143* | 0.0956 |
| | (0.073) | (0.058) | (0.078) | (0.063) | (0.082) | (0.066) |
| Extra Subsidy | | | | | 0.436** | 0.385* |
| | | | | | (0.218) | (0.219) |
| Taxi Subsidy | | | | | 0.0628 | 0.0960 |
| | | | | | (0.184) | (0.177) |
| Free Parking | | | | | 0.181 | 0.139 |
| | | | | | (0.221) | (0.199) |
| Subsidy × GDP per Capita | | | -0.000837** | -0.000616* | -0.000722* | -0.000499 |
| | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Subsidy × Edu Exp R | | | -1.146*** | -1.045*** | -1.067*** | -0.973*** |
| | | | (0.313) | (0.300) | (0.317) | (0.301) |
| Subsidy × Env Exp R | | | -2.086 | -2.106* | -2.346 | -2.433* |
| | | | (1.343) | (1.106) | (1.592) | (1.329) |
| Tier=2 × Subsidy | -0.0752*** | -0.0705*** | -0.0624** | -0.0551** | -0.0587** | -0.0513* |
| | (0.027) | (0.024) | (0.029) | (0.027) | (0.029) | (0.027) |
| Tier=3 × Subsidy | -0.0569** | -0.0566** | -0.0416 | -0.0368 | -0.0328 | -0.0286 |
| | (0.026) | (0.025) | (0.033) | (0.032) | (0.034) | (0.033) |
| Tier=4 × Subsidy | -0.0919*** | -0.103*** | -0.0716 | -0.0765* | -0.0624 | -0.0672 |
| | (0.034) | (0.034) | (0.043) | (0.042) | (0.045) | (0.042) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City & Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 3501 | 3347 | 3501 | 3347 | 3501 | 3347 |

Standard errors in parentheses

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

Table 30: Results for $ln(Num/Pop)$ with Lagged Dependent Variables