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碩士論文

Master's Thesis

中國汽車限購政策對新能源汽車市場份額的影響—以差中差法進行研究

The impact of the Automobile Purchase Restriction Policy on market share of new energy vehicles in China – Estimation under the difference-in-differences method

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摘要

隨著中國經濟的快速成長，消費者對購買汽車的需求也跟著增加，衍生出嚴重的交通擁堵和空氣污染問題。為解決這些問題，上海於 1994 年率先實施了《汽車限購政策》，期望能控制每個月新登錄的汽車數量。此後，許多中國一線城市也陸陸續續於 2010 年至 2014 年期間出台了汽車限購法規。然而，雖然政策實施最初的目的是在控制汽車數量，但再後來卻也被認為是促進新能源汽車發展的關鍵推力之一。

本研究搜集了 2011 年 1 月至 2015 年 12 月間的中國月登陸新增車輛數據。並且採用“差中差”法進行研究，選擇北京，貴陽，廣州，天津，杭州，以深圳六個汽車限購城市作為為實驗組，而其他所有非限制城市為對照組，旨在驗證汽車限購政策確實能為新能源汽車的市場帶來幫助。實驗結果顯示，在政策實施後，實驗組的新能源汽車銷售份額成長顯著的高於對照組的汽車銷售份額成長，證實汽車限購政策確實對推動新能源汽車的市場有正面的影響，特別是在插電式混合動力汽車的效果更為明顯。另外，透過觀察政策實施後一段時間的政策效果還可以發現，該政策的長期效果會比其短期效果來的更理想。

關鍵字：汽車限購政策、新能源汽車

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Abstract

In China, the rapid economic growth brought a huge traffic demand, resulting in traffic congestion and air pollution problems. For dealing with these problems, Shanghai first implemented the "Automobile Purchase Restriction Policy" to control the number of newly registered cars in 1994. Afterward, many cities also introduced the regulations one after another during the period between 2010 and 2014. However, apart from its initial purpose of controlling the number of cars, the policy was later considered also to be one of the critical forces in promoting the development of new energy vehicles.

This paper collects the monthly new registered vehicles data in China dated from January 2011 to December 2015, then selects six restricted cities, Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen as the treatment group and all the other non-restricted cities as the control group. By adopting the "Difference-in-Differences" method, this paper aims to verify whether the policy really impacts the NEVs market. The results turn out that after the implementation of the policy, the growth of the market share of new energy vehicles in the treatment cities is significantly higher than that of in the control cities, which means that the policy does positively affect the market of the NEVs, especially in the plug-in hybrid electric vehicles sector. Furthermore, when observing the overtime effect after the policy is implemented, it can also be found that the long-term effect of the policy is greater than its short-term effect.

Keywords: Automobile Purchase Restriction Policy, New Energy Vehicles

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1. Introduction

1.1 Background

According to the 2012 International Energy Agency (IEA) report, global carbon dioxide emissions exhausted by energy consumption reached 31.6 billion tons, showing a 1.4% increase, which is the highest rise throughout history, as compared with 2011. Producing about 25% of global total emissions a year, China was the country that accounted for the largest proportion of carbon dioxide emissions. Among all sectors, car fume was one of the culprits causing the most serious air pollution, and rapid growth of the automobile industries made the situation even worse. In order to reduce the dependence of the automobile industry on petroleum, and cut pollutant emissions, replacing traditional fuel cars with new energy vehicles (NEVs) is absolutely one of the solutions (Hao et al., 2010). Thus, many countries have begun to develop NEVs industries, and the China government has also been making effort to promote NEVs to deal with air pollution problems and reduce dependence on petroleum in recent years.

The preparation work related to NEVs in China has begun in the 1990s. However, the definition of the NEVs as well as the development plans associate with NEVs in China have not been cleared until the “Energy-Saving and New Energy Vehicle Industry Development Plan (2012-2020)” issued by the State Council in 2012 (Guo et al., 2014). According to the Plan, NEVs refer to vehicles that adopt new types of power systems or are mainly driven by new energy sources, which include battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and fuel cell vehicles (FCVs). And It was expected that, by 2020, the production capacity of domestic BEVs and PHEVs can reach 2 million units, and the cumulative production can exceed 5 million vehicles.

In the early stages of NEV industry development, the China government was facing obstacles with inferior core technologies, immature products, and the lack of monitoring as

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well as evaluation systems. Thus, in spite of some preferential policies have been issued, the market share of NEVs was still pretty small (Gong et al., 2013). Moreover, most of the customers were still not quite familiar with NEVs. They were more inclined to stand on the sidelines because they still in doubt of many issues, such as the limited choices of brands and models, safety and quality issues, high purchase and maintenance costs, as well as the incompleteness of the charging infrastructure for NEVs (Guo et al., 2014).

For enhancing the attraction of NEVs toward consumers and achieved the goal, the China government, on one hand, continuously developed new production techniques, and actively built-up basic charging facilities to reduce the costs of NEVs on both the manufacturing side and the using side. On the other hand, they released a series of policies such as tax deductions and subsidies, providing comprehensive support for the NEVs industries. Among these measures, the "Car Purchase Restriction Policy" (CPRP) is one of the main momentums pushing the sales of NEVs (Wang et al., 2020). Thanks to the endeavor of the China government, the development of NEVs in China ushered in explosive growth during this period. The annual sales volume of NEVs ascended from about 8,000 in 2011 to more than 330,000 in 2015, and the cumulative sales of NEVs was almost there for the 500,000 vehicles target mentioned in "Energy Conservation and New Energy Vehicle Industry Development Plan (2012-2020)". China, as the result, has become one of the countries that have the best sales of NEVs in the world (Wang et al., 2017).

1.2 Car Purchase Restriction Policy

In fact, China is not the first country to adopt the CPRP for working out the traffic congestion and air pollution problems. As early as 1990, Singapore has already had the experience of posing the restriction policies on the car purchase. At that time, Singapore was dedicated to limiting the growth of car usage as well as ownership in order to solve the traffic congestion issue, and "Vehicle Quota System" was one of the measures they tried. By forcing potential customers to bid for the limited number of certificates of entitlement, which is

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permission of driving on the road, the system has effectively achieved the goal of controlling the number of new vehicles and, thereby, eased the traffic loading on their roads (Olszewski and Turner, 1993). Being the first country to apply the CPRP, Singapore's successful experience gave a lesson to other countries that were struggling with the same issue (Koh and Lee, 1994).

In 1994, Shanghai became the first city to regulate the number of cars in China. At that time, China's rapid economic progress brought a huge traffic demand, leading to a dramatic increase in car ownership. However, the transportation facilities and management standards in the city could not keep up with the development of the automobile industries, leading to the road systems failed to bear the traffic load (Hao et al., 2010). In order to solve the increasingly serious traffic jam and environmental pollution problems, Shanghai City implemented the “License Plates Auction” to control the quantity of newly registered cars, namely the CPRP. Afterward, seven cities, including Beijing, Guiyang, Guangzhou, Shijiazhuang, Tianjin, Hangzhou, and Shenzhen, also introduced the regulations one after another during the period between 2010 and 2014 to strictly controlled the quota of cars in the city.

There mainly are two ways to determine which individual or unit can win the license plate and gets an opportunity to purchase vehicles: auction and lottery. The detailed policy implementation time and restrict methods of each city are shown in Table 1. As it can be witnessed, Shanghai is the only city that people can obtain license plate only through auction. On the contrary, Beijing and Guiyang are representative cities that run the policy only via lottery. The remaining cities, Guangzhou, Tianjin, Hangzhou, and Shenzhen, combine both auction and lottery as their restriction method.

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Table 1. Automobile Purchase Restricted Cities

City	Since	Restrict methods
Shanghai	1994	Auction only
Beijing	2010/12/23	Lottery only
Guiyang	2011/07/12	Lottery only
Guangzhou	2012/06/30	Both auction and lottery
Shijiazhuang	2013/06/08	Restriction on the third car of each family and agency
Tianjin	2013/12/16	Both auction and lottery
Hangzhou	2014/03/26	Both auction and lottery
Shenzhen	2014/12/29	Both auction and lottery
Hainan	2018/05/16	Both auction and lottery

Every year, each city will offer different numbers of license plates regarding its situation, and appropriately allocate those "incremental indicators" into three different sectors: NEVs, ordinary vehicles, and vehicles for units. The auction is held once a month. The consumer who wants to participate in the auction and win the indicator can bid through an online quotation. The result of the auction follows the principle of "price priority, time priority", that is, within the number of indicators, the bidder who offers a higher final valid quotation is going to win the bid. If the final valid quotations are the same, then the bidder who makes the final valid quotation first will get the indicator. As for the lottery, it is usually held once a month. Every resident, unit, or expatriates who meet the application requirements has the qualification to apply for an application code through the designated website or counter. After the application has been confirmed by the authorities, those codes will be automatically put in the base of the lottery. Via lottery, applicants have the opportunity to obtain the indicator and purchase their car. The codes that have not obtained the indicator will be transferred to the lottery base and participate in the lottery directly in the next period. The quotas which are not configured

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for each time will be postponed to the next allocation, and finally invalidated at the end of the year.

When an increasing number of people and units wanted to apply for limited allocations, the chances of winning indicator were getting lower and lower. Owing to the implementation of the CPARP, the costs, no matter calculate in money or time, of receiving indicators through auction and lottery constantly rose due to people's high demand for cars (Tang et al., 2019). Therefore, the separate lottery channel for NEVs provided a huge benefit for people who eager to own a car. By September 2015, Premier of the State Council, Li Keqiang clearly stated that “all localities should not impose driving and purchasing restrictions on NEVs, and cities that have already implement the policies should cancel those restrictions” in the meeting of the State Council. Afterward, the cities that posed restrictions on NEVs canceled those limitations immediately. In this way, China government further established the goal of supporting the development of NEVs. The consumers who want to buy NEVs can obtain the indicator directly without participating in the auction and lottery. Due to the reason that license plates of NEVs were much easier to be obtained, more and more consumers were inclined to turn to buy NEVs rather than traditional cars.

1.3 Research Motivation and Purpose

By 2015, China surpassed the United States and Europe, becoming the world's largest country in the NEVs sales market. And in accordance with China Association of Automobile Manufacturers (CAAM) statistics, restricted cities occupied five out of the top ten cities in terms of annual sales of NEVs, with their sales volume standing for almost 50% of the total NEVs sales throughout the whole China.

The purpose of this paper is to verify whether the CPRP can really encourage people to purchase NEVs, rather than just only the result of being affected by other promotional policies or environmental factors. So far, there have been tons of studies on the CPRP, while many of them are focusing on the impact of the CPRP on the sales of fuel vehicles and its effectiveness

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in improving air pollution problems rather than on NEVs. In addition, many studies have focused on the impact of policies in a specific individual city instead of looking at the overall effects of the policy. Last but not least, many studies may fail to concern the interference of external economic factors when selecting research methods, leading to bias in the estimation results. In this case, "Difference in differences" (DID) method is especially suitable to deal with the problems.

Thus, this paper will apply the DID method to measure the changes in the market share of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) within the total sales of vehicles after six restricted cities, including Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen, imposed the CPRP. Apart from that, this paper will also further look for the continuous effect on the six restricted cities respectively after the implementation of the CPRP, aiming to explore its short-term and long-term impact on the NEVs market. By doing so, it is hoped that a more comprehensive picture of the influence of the CPRP on the development of the NEVs can be given. One of the main advantages of choosing market share instead of purely selecting sales volume as the target is that, by doing so, it can reduce the interference of some external macro factor, such as income growth, economic growth, as well as industry cyclical fluctuations, and so on (Ma et al., 2017), and help observe the phenomenon that is really concerned about.

1.4 Framework

The content of this paper is consisting of five parts. After providing some background knowledge of the CPRP and the effects it might cause on the development of the NEVs industry in China, the second parts of this paper are going to review some previous studies on the CPRP as well as the DID model. In the third part of this paper, the data sources and all the variables used in this study will be clarified. Furthermore, a detailed explanation of the research design and the research methods will be given in this part as well. Afterwards, the results of the research will all be presented in the fourth part, and, finally, conclusions will be

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drawn based on the results of the study.

2. Literature Review

2.1 The Review of Car Purchase Restriction Policy

As mentioned in the background above, the traffic as well as the air pollution problem led by the excessive number of cars due to the fast economic-growth is a critical problem that many countries are suffering. Different countries may use different methods to solve this problem according to their different conditions, and the CPRP is one of the ways to deal with this issue. The release of the CPRP in China can be traced back to 1994, by means of controlling the number of license plates through the auction system. Different from Shanghai's auction system, Beijing first adopted the lottery system in 2011 to determine who can obtain the qualification to register a new car. Subsequently, many other cities have successively implemented car purchase restrictions through either auction or lottery systems, or even executed in both ways.

Hao et al. (2010) compared the policy in Beijing and Shanghai, the two metropolises in China that issued the car purchase restriction policy, and estimated their impacts on the consumption of fuel vehicles. It is argued that, through auctions, the issue of license plates through public auction is unfair because only citizens with high income are able to win the auction and afford a car. In comparison, the lottery system adopted in Beijing seems to be fairer. On the other hand, in the lottery system, the recipient of the cars will be randomly selected within the poll of participants, while, under the auction system, car license plates can usually be assigned to those who have the highest willingness to pay (Yang et al., 2014). Nonetheless, both policies issued in Beijing and Shanghai did reduce the consumption of fuel vehicles, with each had its own advantages. In Beijing, the policy provided a limited but immediate reduction in fuel consumption. On the other hand, the limitation in Shanghai provided a large potential for fuel conservation in the long run.

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There also have some researches been studied on the effectiveness of the CPRP to control the number of newly registered cars. Liu et al. (2020) adopted the logistics model to measure the private vehicle ownership per thousand people in the four restricted cities, Beijing, Tianjin, Guangzhou, and Shanghai, after the implementation of the CPRP. The result demonstrated that the CPRP can effectively curb the growth of newly registered cars in those cities. Feng et al. (2012) took the time 2003 when the CPRP was well-established instead of 1994, the time that CPRP was first implemented, to run the DID estimator for assessing the impact of the license plate auction on the ownership of private cars in Shanghai. It also came to the conclusion that the CPRP did reduce the growth of the number of private cars.

At the time that the CPRP limits the growth of traditional fuel vehicles number in China, NEV is, however, not within the scope of restriction. As the policy makes NEVs superior to fuel cars no matter in purchase or usage, the CPRP may to a certain extent affect the preference of consumers. Those gaps in the demand for traditional cars created by CPRP can be filled by NEVs, and thereby rebalancing the supply and demand between the NEVs and fuel vehicles markets (Ma et al., 2017).

Benefiting from the privileges brought by the CPRP, NEVs began to come into people's vision, and gradually changed consumers' car purchase choices. Wang et al. (2017) established the structural equation model to evaluate the factors that may improve the preferences of people to buy NEVs. The results turned out that the policy privileges are one of the most critical factors that may cause a positive influence on NEVs purchase intention, and the CPRP is the one that especially phenomenal among all policies. Wang et al. (2020) analyzed the interests of consumers in NEVs by collecting and recording online consumer comments in China and found out that national policy played an important role in pushing consumers to purchase NEVs. And again, the licensing regulations, namely the CPRP, were one of the main momentums of consumers' concern. Wang et al. (2017) also showed that, under the CPRP, consumers would more inclined to purchase NEVs with free license plates rather than

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choosing traditional vehicles. Moreover, by comparing the sales of BEV and PHEV in restricted cities, they further found out that consumers may have slightly different preferences for NEVs sub-collections, which indicates that the CPRP may possibly have varying degrees of impact on the market share of BEV and PHEV. Anyway, all these pieces of evidence proved that the CPRP may not only reach the aim of constraining the new registered number of fuel cars, but also promoting the development of the NEVs market. However, many of the statistical methods used in the studies above may ignore the effect of time series and many other external factors, leading to some bias in their estimation (Wang et al., 2011).

2.2 The Review of Difference in Differences

When analyzing the influence of the CPRP on the market share of NEVs, there are factors needed to be taken into concern. For instance, customers in different cities with or without the CPRP may have different standards, such as wealth, buying habits, and so on. Even in the same city, the market share of NEVs might also be affected by factors other than the CPRP over time. Some of these changes and characteristics may difficult to quantify and collect, and some cannot even be comprehensively observed. However, they can often affect the results of the research. Therefore, purely putting all the observations together and discussing them directly is likely to misappraise the effects of the intervention policy (Fredriksson and de Oliveira, 2019), and this is also one of the biggest challenges facing by the studies above. Nonetheless, “Difference in Differences” (DID) approach is an especially suitable tool to deal with the problem under such circumstances.

The DID estimator is a statistical technique basing on the pre-post and the treatment-control comparisons and is believed to be first applied by John Snow in his 1855 studies. The main concept behind the DID approach is to tell the influence of the specific treatment on the observed object and the degree of the influence by observing the differences between “treatment group” versus “control group” before and after the occurrence of a certain event in a non-experiment situation (Angrist and Pischke, 2008). In addition, for the reason that the

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overtime changes and the heterogeneity between groups apart from treatment have all been controlled through the fixed effect terms, the causal effect of treatment on the treatment group can be observed more easily (Wooldridge, 2007).

One of the most classic examples of applying the DID model is that Card and Krueger (1994) applied the method to evaluated the impact of minimum wages on the employment of the fast-food industry in New Jersey. They conducted a series of the telephone interview with a total of 410 restaurants in New Jersey, where was going to raised its minimum wage, and eastern Pennsylvania, the neighboring city that did not change its minimum wage and shared similar seasonal patterns of employment with New Jersey. Via asking the same information such as the wages, the level of employment, and prices charged before-after the rise of the minimum wage, they found out that there was indeed a change in the differences between the two cities pre-post the rise of the minimum wage. The result showed that the increase of minimum wage in New Jersey led to employment in the fast-food industry to appreciate by 2.76 employees per restaurant.

Nowadays, the DID estimator has been widely used in impact assessment in the fields of public policy evaluation. Yet, there have been thousands of studies using this method to conduct research. Thus, here it won’t be gone into detail, whereas only some of the studies with experimental designs close to this paper are going to be reviewed.

For instance, Tan et al. (2018) applied the DID method to analyze the effect of the "Ten Cities, Ten Thousand New Energy Vehicles Project” on reducing urban air nitrogen dioxide concentration in China. The research recovered that, although the reduction is very limited and is not enough to meet the expectations of the policy, the policy did reduce urban air nitrogen dioxide concentration. By continuously tracking the treatment effect of the policy after the implementation time, the result also exhibited that the contribution of the policy to the reduction of carbon dioxide concentration has become more and more effective over time. Wang (2017) ran the DID model to compare the changes between the treatment group and

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the control group before and after the implementation of the CPRP for evaluating the impact of the policy on the market share of the self-owned brand vehicles in Beijing. Based on the previous research methods, the study added the effect of time trend to exclude the possible changes in the market share of self-owned brands as time going. Finally, it is found that the effect of the CPRP on the market share of the self-owned brand automobile will become greater and greater over time. Both of the two studies above built the DID model to observe changes in policy effects over time. In this paper, the same experiment will also be used to evaluate the long-term and short-term effects of the CPRP on the market share of NEVs in the restricted cities.

However, for some of the real-world situations, the treatment across a group of observations may not happen at the same time. In such cases, the multi-period DID model can still be well applied to deal with the problem, and that's one of the reasons that make the DID method to be a suitable policy evaluating technique is that it cannot only be used to compare policy effects at a single point of time, but also be applied to examine the average treatment effects brought about by different observations at multiple treatment times. Beck et al. (2010) applied the DID approach with multiple treatment times, aiming to measure the relationship between deregulation of banks and income inequality in the United States. In the study, they scraped the data from 48 states in the United States plus the District of Columbia from 1976 to 2006, however, since each the deregulation policy in each state was inevitably implemented at different time periods, the multi-periods DID model is required to be applied. The results of the study found that these deregulation policies truly increased the wages of unskilled workers, but had merely no effect on groups with incomes above the median level. Therefore, overall, it narrowed the gap of income equality of the entire American society.

In this paper, the multiple treatment times DID methods will be established, with the consideration of the CPRP as the treatment, the restricted cities as the treatment group, and the non-restricted cities as the control group. The first part of the experiment will aim to

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exanimate whether the CPRP will, indeed, affect the market share of NEVs. Whereas, the second part of the experiment will dig into the influence of the CPRP on each city to compare the overtime market share changes in the six purchase restriction cities. It is hoped that the comparison between the changes in the market share of NEVs within restricted cities and non-restricted cities before and after the policy was implemented can help evaluate the impact of the CPRP does on NEVs.

3. Data and Research Method

3.1 Data Sources

The data used in this paper comes from "China monthly new registered vehicles" released by "Vehicle Registration Administration Office", which contains clear sales information for various types of cars across most of the regions in China. Although the data recorded in this data resource may to some extent differ from the data provided by the China Association of Automobile Manufacturers (CAAM) that is mentioned in the previous due to the different statistic calculated methods, the data from the China monthly new registered vehicles data contains detailed data that lasts for a period of time, which can better reach the research needs of the DID models where requires multiple sample data in multiple time points. Therefore, this paper decided to adopt the Vehicle Registration Administration Office data source rather than the source from CAAM.

So far, a total of 9 cities in China have issued the CPRP, including Shanghai, Beijing, Guiyang, Guangzhou, Shijiazhuang, Tianjin, Hangzhou, Shenzhen, and Hainan. However, this paper will only select six of them, namely Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen, as the treatment group. The reason for choosing only the above six cities instead of all the limited cities is that (1) The implementation time of the automobile purchase restriction policy in Shanghai is relatively early. When adopting the DID method, it is necessary to have complete data of all the observations in a period of time. However, in 1994, the

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concept of NEVs has not been popularized yet and, thus, there is still a lack of reliable statistics of the NEVs in China. (2) Same here, as Hainan Province issued CPRP just in 2018, it is difficult to obtain the complete data. (3) The restriction methods in Shijiazhuang only set a limit on the third cars purchased by families and units, which is totally different from the auction and lottery restrictions that are commonly used in other restricted cities. Obviously, such limitation does not seem to be as strong as the restrictive methods adopted by other cities. In order to avoid the deficiencies in these data or the differences in policy implementation leading to possible deviations in the research results, the data of Shanghai, Hainan, and Shijiazhuang will be removed, and will not be covered in the following discussion. Finally, apart from these cities, all the remaining 406 cities will be set as our control group.

3.2 Descriptive Statistic

The sales of NEVs have grown rapidly in recent years. As the figure shown in Figure 1, in 2010, about 1,700 BEVs and PHEVs were sold. From 2012 to 2013, although the sales of BEVs and PHEVs slightly increased from around 15,000 to 16,000, the market share dropped by 0.01%, which represents that although more BEVs and PHEVs are being sold, consumers may not be more inclined to buy BEVs and PHEVs rather than fuel cars. Nevertheless, the efforts of the Chinese government to promote the development of NEVs have never been interrupted. It was not until 2014 that the sales volume and market share of BEVs and PHEVs ushered in explosive growth. By 2015, this number has already reached more than 330,000 BEVs and PHEVs a year. Besides, it can be found that the sales of PHEVs are normally higher than that of BHEVs on average in the past few years.

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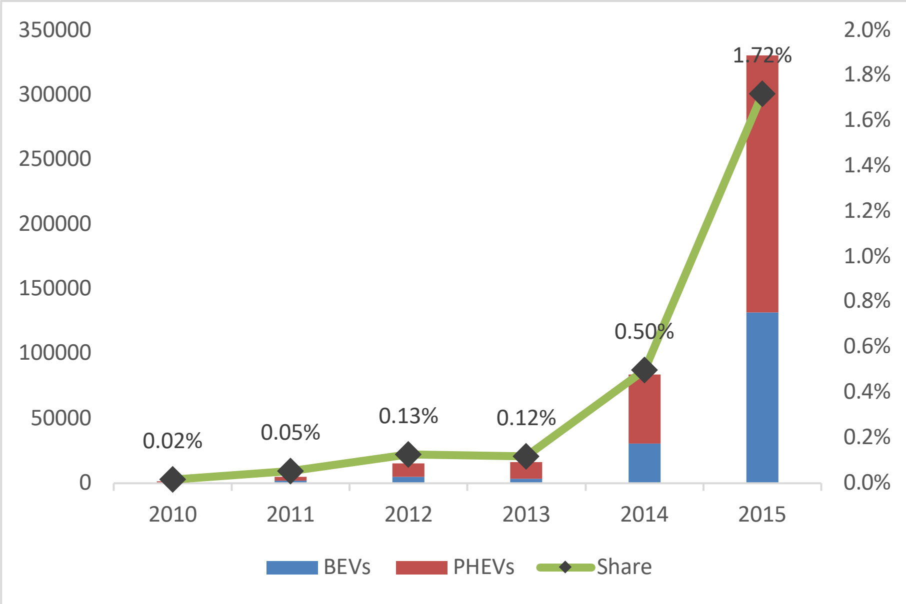
Figure 1. The annual sales and market share of BEVs and PHEVs in China from 2010 to 2015



As for figure 2, figure 3, and table 2 are the changes over a period of time from 2010 to 2015 in the market share of BEVs and PHEVs in cities with purchase restriction. By observing these descriptive statistics, they show that, among the cities under the restriction of CPRP, Hangzhou has the highest average in terms of market share in BEVs, and occupies the second place in PHEVs, with the market share of both type of cars concentrated in a few particular months. On the other hand, experiencing the rapid growth of BEVs and PHEVs market share during 2015, Shenzhen and Guangzhou have a relatively low NEVs market in the beginning, while become the restricted cities with the highest market share of BEVs and PHEVs at the end of 2015. In contrast, the market share of Guiyang has been in a sluggish situation. Even after the implementation of the CPRP, its average market share is still lower than the average level of other non-restricted cities. All in all, apart from Guiyang, the remaining restricted cities all show a greater growth in the market share of NEVs than those in non-restricted cities after the implementation of the CPRP.

Comparing the market share of each restricted city with other non-restricted cities, it can also be witnessed that the market share of BEVs and PHEVs in each city has grown differently.

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In Guangzhou, Shenzhen, and Tianjin, the market share of PHEVs has grown especially faster than that of BEVs. Last but not least, when adding the time point that the policy is introduced, it can be witnessed that after the implementation of the CPRP in the restricted cities, the growth of market share may not turn out immediately. However, if observe the changes over time, its growth may be found more and more obvious. In the following study, the DID method is going to applied to test whether the greater increase in the market share of NEVs in restricted cities than in the non-restricted city can be attributed to the implementation of CPRP.

Figure 2. The overtime market share changes of BEVs in restricted cities and non-restricted cities from 2010 to 2015

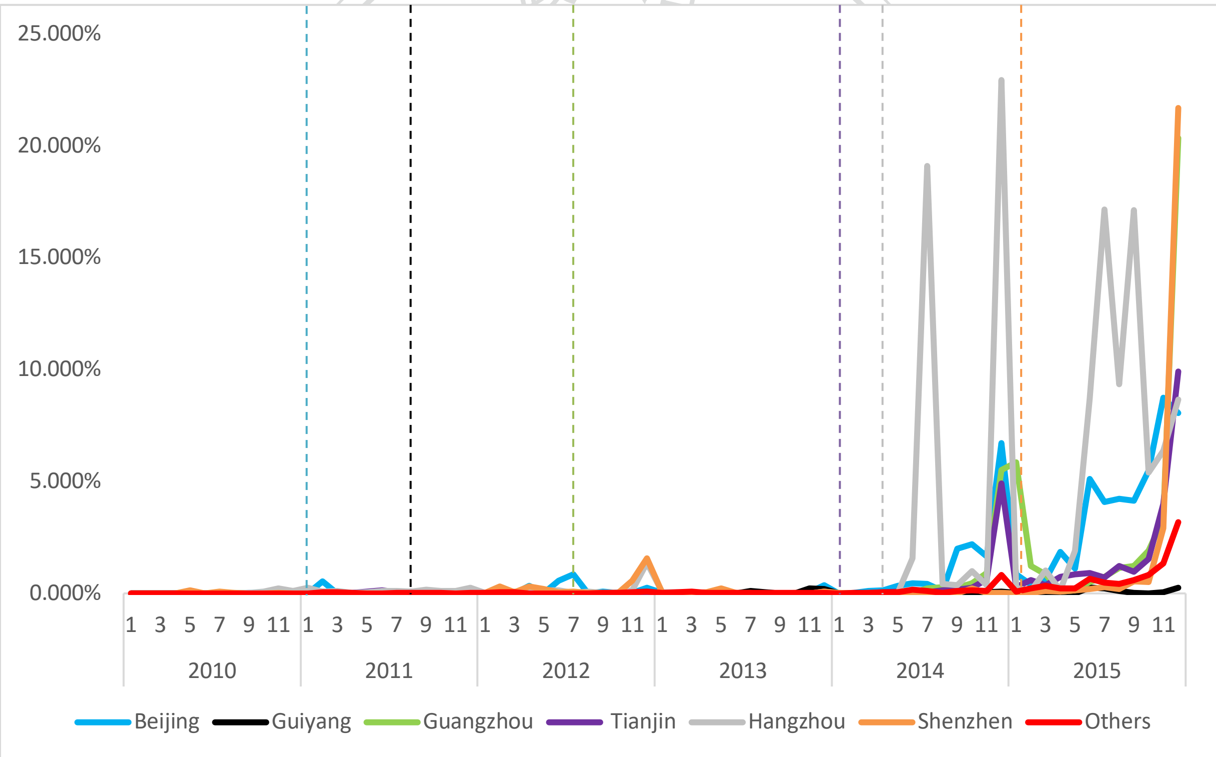

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Figure 3. The overtime market share changes of PHEVs in restricted cities and non-restricted cities from 2010 to 2015

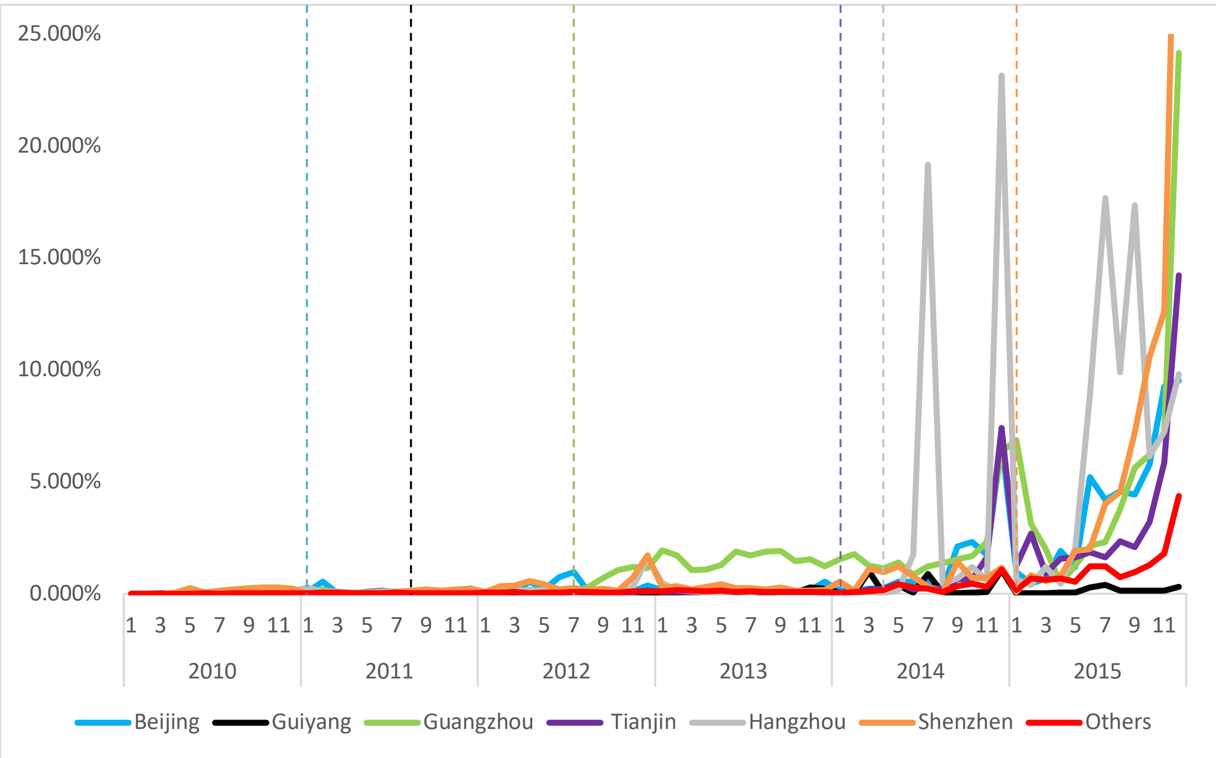

Table 2. The annual market share of BEVs and PHEVs in restricted cities and non-restricted cities in China from 2010 to 2015

Type	Year	Beijing	Guiyang	Guangzhou	Tianjin	Hangzhou	Shenzhen	Others
BEVs	2010	0.00%	0.00%	0.00%	0.00%	0.04%	0.02%	0.00%
	2011	0.06%	0.00%	0.00%	0.06%	0.12%	0.00%	0.02%
	2012	0.18%	0.00%	0.00%	0.01%	0.18%	0.27%	0.03%
	2013	0.04%	0.05%	0.00%	0.00%	0.02%	0.04%	0.03%
	2014	1.18%	0.01%	0.64%	0.53%	3.82%	0.04%	0.13%
	2015	3.73%	0.08%	3.12%	1.85%	6.36%	2.22%	0.72%
PHEVs	2010	0.01%	0.01%	0.02%	0.01%	0.05%	0.14%	0.01%
	2011	0.09%	0.02%	0.05%	0.07%	0.13%	0.08%	0.03%
	2012	0.29%	0.01%	0.42%	0.06%	0.24%	0.43%	0.06%
	2013	0.18%	0.10%	1.55%	0.05%	0.11%	0.25%	0.10%
	2014	1.29%	0.30%	1.87%	0.99%	3.94%	0.76%	0.30%
	2015	4.02%	0.14%	5.43%	3.27%	6.81%	7.06%	1.19%

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3.3 Variables

3.3.1 Dependent variable

Market share

This paper uses the monthly data of newly registered vehicles, which can represent the number of car sales in each month. The data includes the classifications of fuel cars, electric battery vehicles (BEVs), hybrid electric vehicles (PHEVs), and so on. Therefore, monthly market share can be calculated by using the sales of EVs and PHEs divided by the monthly sales of cars in total.

3.3.2 Explanatory variables

City

The main purpose of this paper is to test the changes in the market share of NEVs after the CPRP is issued in the restricted cities. Therefore, it is necessary to establish a dummy variable “city”. There are totally 412 cities adopted in the study, of which the dummy variable of the restricted cities is set to be equal to 1, while that of the remaining cities is set to be equal to 0.

Time

In addition, the dummy variable "time" is also required. Here, the time variable is measured in months, starting from January 2010 and ends in December 2015. Therefore, there will be 72 time-dummies in total. In terms of the setting of time-dummies, the months after the CPRP is implemented in the restricted city are set to be 1, otherwise are set to be 0. To be specific, the CPRP in Beijing was valid in January 2011, so the months after the policy is implemented in this city are set to be equal to 1; The policy in Guiyang was valid in July 2011, so the months after the policy is implemented in this city are set to be equal to 1; The policy in Guangzhou was valid in July 2012, so the months after the policy is implemented in this city are set to be equal to 1; The policy in Tianjin was valid in January 2014, so the months after

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the policy is implemented in this city are set to be equal to 1; The policy in Hangzhou was valid in April 2014, so the months after the policy is implemented in this city are set to be equal to 1; The policy in Shenzhen was valid in January 2015, so the months after the policy is implemented in this city are set to be equal to 1. The rest of the months are all set to be equal to 0.

The interaction of city and time

Through multiply the city dummy and the time dummy, the interaction term of the restricted city and the months after the CPRP is introduced will be 1, otherwise will be 0. By using the DID method, we can see whether the market share of BEVs and PHEVs in the restricted cities will be affected after the policy is introduced.

3.4 Research Design

The experiment consists of two parts. The first part of the test is going to apply the multi-periods DID model to evaluate the impact of the CPRP on the market share of NEVs by calculating the average treatment effect among the treatment cities. Overall, it is anticipated that the policy will have a positive impact on the promotion of NEVs. The second part of the experiment will keep the track on the impact of the CPRP in each purchase restriction city. In this way, it is hoped to deeply explore the overtime influences of the CPRP in different restricted cities.

3.4.1 Difference in Differences

The basic DID research framework is normally expressed from the data of two groups, treatment group and non-treatment group, as well as two time periods, pre-treatment period and post-treatment period. Under such experimental design, the estimation of the treatment's influence on the group of interest can be showed as follow equation (Fredriksson and de Oliveira, 2019):

$$DID = \left(\bar{y}_{c=1,t=1} - \bar{y}_{c=1,t=0}\right) - \left(\bar{y}_{c=0,t=1} - \bar{y}_{c=0,t=0}\right)$$

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In the case of this paper, $\bar{y}$ represents the market share of NEVs; The index c is the dummy of treatment group and the control group, where c equals to 1 state for the restricted cities, whereas c equals to 0 represents the non-restricted cities; The index t is the time dummy, where t is 0 before the CPRP is carried out, and t will be 1 after the restricted cities receive the treatment. Finally, the DID can be calculated from the double difference of the outcomes of pre-post treatment in the treatment cities, and that of before-after treatment in the control cities.

However, the above description of the DID can only tell its basic concepts, but does not contribute to the assessment of the DID approach. Hence, in the previous researches, people commonly used the regression analysis as the setting of the DID estimator. Similarly, this setting can also be adopted in the DID with multiple treatment time periods (Fredriksson and de Oliveira, 2019), and the equation can be written as follow:

$$Share_{ct} = \alpha_c + \alpha_t + \beta R_{ct} + \varepsilon_{ct}$$

Where α_c、α_t refers to the fixed effects of city c and time t, respectively. The dependent variable $Share_{ct}$ is the market share of NEVs by the month t in the city c. This figure is calculated by putting the sales of NEVs in city c as the numerator, and divided by total vehicles sales in city c as the denominator within the month t. ε_{ct} is an error term. As the key part of the entire model, βR_{ct} represents the impact of the CPRP on the market share of NEVs after the policy is introduced. The variable R_{ct} is the interaction of the city dummy and time dummy, which makes it also a dummy variable. c represents the city, and if the city c is the restricted city, c is set to be equal to 1, otherwise, it will be equal to 0. Besides, t represents time, and t is set from January 2010 to December 2015 for a total of six years. The starting time of Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen is counted in January 2011, July 2011, July 2012, January 2014, April 2014, and January 2015 respectively. The value of t is set to be equal to 0 before the policy is implemented, and be equal to 1 after implementation. Finally, β infers the DID coefficient of the month after the car purchase

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restriction, that is to say, β measures the change in market share of NEVs in restricted cities after the implementation of policy, compared with that of in non-restricted cities.

Therefore, if all the six purchase-restricted cities are placed in the treatment group for estimation at the same time, then the result of the DID estimator will represent the average treatment effect of the policy on the market share of NEVs in six treatment cities. On the contrary, if the research purpose is to understand the respective effects of the CPRP on the market share of NEVs in each of the six restricted cities, they should be put in the DID estimator one by one, and be calculated separately.

3.4.2 Average treatment effect on the treated

When establishing the DID model with multiple treatment times, evaluating the average treatment effect on the treated (ATT) rather than the causal effect of each unit is usually more of a concern since the average causal effect of each unit can be quite ambiguous (Angrist and Pischke, 2008). The average treatment effect on the treated is measured by the average outcome of each unit that actually receives the treatment, and can be expressed by the following equation (Egami and Yamauchi, 2019):

$$ATT = E[Y_{ct}(1) - Y_{ct}(0)|G_c = 1]$$

Where $Y_{ct}(1)$ states for the market share of NEVs for each time period t if city c has imposed the CPRP treatment. $Y_{ct}(0)$ is the potential market share of NEVs in the time period t if city c has not received the CPRP treatment. Hence, $Y_{it}(1) - Y_{it}(0)$ means the difference in the causal effect of CPRP on the market share of NEVs for a single restricted city in time t. Under the condition of $G_i = 1$, where the treatment group is selected, the causal estimation, ATT, represents the average of all the individual causal effects for the units on treated. As the result, the estimated ATT through the DID model will be the average treatment effect of the CPRP on all the six purchase-restricted cities, rather than its influence in a specific purchase-restricted city.

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4. Results

This paper mainly discusses the impact of CPRP on the market share of EVs and PHEVs. In the first experiment, since the six restricted cities, namely Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen, received the treatment at different times, the research results from the DID method will be the average treatment effect of the CPRP on the market share of EVs and PHEVs in these cities. The estimation is exhibited in table 3. In order to highlight the results that are concerned, the tables omit the fixed effects of 412 cities including the treatment cities and the control cities, as well as the fixed effects of time from January 2011 to December 2015. The remaining term, the interaction of city dummy and time dummy, represents the average treatment effect of the CPRP on the market share of EVs and PHEVs in the treatment cities.

As the figures shown in table 3, the results turn out that the coefficient of the city dummy and time dummy interaction term is 0.0179 in BEVs, and 0.0287 in PHEVs. Besides, their P-values are 0.026 and 0.007 respectively, which are significant at the 0.05 and 0.01 significant level. That is to say, after the introduction of the CPRP, the market share of both BEVs and PHEVs in the restricted cities are significantly higher than that of in the non-restricted cities. To be specific, the market share of BEVs will increase by around 1.8%, while the market share of PHEVs will ascend by 2.9% on average due to the impact of the CPRP.

In the second experiment, this paper tracks the influence of the CPRP on the market share of BEVs and PHEVs in each of the six restricted cities after the policy was implemented. The results are listed in table 4 and table 5. Similarly, the table will also highlight the coefficient of the city dummy and time dummy interaction term, which can most stand for the overtime DID results. Looking into these tables, lag 1 represents the multiplied of the restricted city dummy and the time dummy of the first month after the CPRP was executed, lag 2 implies the multiplied of the restricted city dummy and the dummy of the second month after the policy was implemented, and so on. Therefore, due to the starting time of the policy are not the

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same, the interaction left behind for each restricted city in the following table will be different based on the period they implement the CPRP. The focus of this part of the result will be to observe the changes in the estimated coefficients of these interactions, in order to infer the impact of the CPRP over time. And the robust standard errors are demonstrated in parentheses.

From the figure presented in table 4 and table 5, it can be witnessed that the CPRP policy is not quite effective in promoting the market share of BEVs and PHEVs in the short run. There are many estimated coefficients can even be found negative in the interactions of the first few periods. Besides, the short-term effects of the CPRP in Beijing, Guiyang, and Guangzhou, the restricted cities where implemented the policy in relatively early periods, were comparably insignificant. The reason might be that since NEVs were not yet popular, the monthly sales of NEVs in those cities may often only in single digits or even none, resulting in a not significant result, especially in BEVs sectors.

However, as time going, the influence of the CPRP on the market share of BEVs and PHEVs in Beijing, Guangzhou, Tianjin, Hangzhou, and Shenzhen have all begun to show, changing the estimated coefficients from negative to positive. Although the coefficients may fluctuate in the intermediate processes, they show an upward trend as a whole, which means that the CPRP is getting more and more effective. On the other hand, Guiyang is the only restricted city where its market share of NEVs has not seems to be improved by the CPRP. Thus, generally speaking, it is without a doubt that the CPRP did play a critical role in the development of the market share of both BEVs and PHEVs in the six purchase restriction cities, and the effect of the policy seems to be more effective in the long run rather than in the short run. Finally, comparing the long-term effects of the CPRP on PHEVs and BEVs, it can also be found that the impact of the CPRP on PHEVs is greater than that of on BEVs in all of the restricted cities.

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Table 3. The impact of the automobile purchase restriction policy on the market share of new energy vehicles

Type	Terms	Coef.	Robust Std Err.	t	P>|t|
BEVs	City*time	0.0179	0.0080	2.23	0.026
	Cons.	0.0002	0.0001	1.85	0.065
PHEVs	City*time	0.0287	0.0090	3.19	0.002
	Cons.	-0.0001	0.0001	-1.13	0.259

Table 4. The overtime impact of the automobile purchase restriction policy on the market share of battery electric vehicles in each restricted city

	Beijing	Guiyang	Guangzhou	Tianjin	Hangzhou	Shenzhen
lag 1	0.001%	-0.004%	-0.002%	-0.013%***	-0.093%***	-0.094%***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
lag 2	0.524%***	-0.006%	0.002%	-0.015%***	-0.078%***	-0.091%***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
lag 3	-0.013%	-0.003%	-0.001%	-0.004%	1.471%***	-0.006%
	(0.0013)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)
lag 4	-0.006%	-0.003%	-0.003%	0.026%***	19.019%***	-0.021%
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
lag 5	-0.000%	-0.003%***	-0.011%	0.047%***	0.342%***	0.007%
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
lag 6	-0.000%	-0.003%*	-0.033%	0.014%*	0.289%***	0.015%
	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0003)
lag 7	0.050%***	-0.016%	-0.009%**	0.012%**	0.887%***	0.081%***
	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0002)
lag 8	-0.008%	-0.007%	-0.009%**	0.129%***	0.259%***	0.013%
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)
lag 9	0.091%***	-0.007%	-0.015%**	0.179%***	22.669%***	0.313%***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0005)	(0.0003)
lag 10	0.034%***	0.000%	-0.003%	0.268%***	0.153%***	0.276%***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0003)
lag 11	0.027%***	0.000%	-0.007%	0.346%***	-0.012%	2.529%***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0006)
lag 12	0.011%***	0.000%	0.001%	3.572%***	0.894%***	20.839%***
	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0002)	(0.0017)

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lag 13	-0.018%	-0.003%	0.003%	0.260%***	0.011%***
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
lag 14	-0.009%	0.001%	-0.007%	0.552%***	1.795%***
	(0.0001)	(0.0000)	(0.0000)	(0.0002)	(0.0001)
lag 15	-0.010%	-0.003%	-0.003%	0.314%***	8.532%***
	(0.0001)	(0.0000)	(0.0000)	(0.0002)	(0.0003)
lag 16	0.339%***	-0.004%*	-0.003%	0.696%***	16.957%***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)
lag 17	0.011%***	-0.013%	-0.005%	0.799%***	9.173%***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0002)
lag 18	0.556%***	-0.034%	-0.003%	0.777%***	16.922%***
	(0.0000)	(0.0002)	(0.0001)	(0.0003)	(0.0003)
lag 19	0.838%***	-0.011%	0.020%***	0.569%***	5.150%***
	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0003)
lag 20	-0.002%**	-0.011%*	0.002%	1.105%***	5.989%***
	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0006)
lag 21	0.084%***	-0.017%*	0.003%	0.802%***	7.794%***
	(0.0000)	(0.0001)	(0.0000)	(0.0003)	(0.0017)
lag 22	0.028%***	-0.005%	0.043%***	1.351%***	
	(0.0000)	(0.0000)	(0.0000)	(0.0003)	
lag 23	-0.002%	-0.008%*	-0.004%	3.678%***	
	(0.0001)	(0.0000)	(0.0001)	(0.0006)	
lag 24	0.211%***	-0.003%	0.003%	9.116%***	
	(0.0002)	(0.0000)	(0.0001)	(0.0017)	
lag 25	0.005%	0.117%***	0.192%***		
	(0.0001)	(0.0000)	(0.0000)		
lag 26	-0.008%	0.056%***	0.282%***		
	(0.0001)	(0.0000)	(0.0000)		
lag 27	-0.019%**	-0.004%	0.242%***		
	(0.0001)	(0.0000)	(0.0000)		
lag 28	-0.001%	-0.005%	0.411%***		
	(0.0000)	(0.0000)	(0.0001)		
lag 29	-0.007%*	0.216%***	0.900%***		
	(0.0000)	(0.0000)	(0.0001)		
lag 30	0.003%	0.171%***	5.310%***		
	(0.0000)	(0.0001)	(0.0005)		
lag 31	0.004%	0.002%	5.857%***		
	(0.0000)	(0.0000)	(0.0001)		

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lag 32	0.023%***	0.000%	1.179%***		
	(0.0000)	(0.0000)	(0.0002)		
lag 33	-0.001%	0.001%	0.804%***		
	(0.0000)	(0.0000)	(0.0002)		
lag 34	-0.004%	-0.012%***	0.051%***		
	(0.0000)	(0.0000)	(0.0001)		
lag 35	0.034%***	-0.014%***	0.100%***		
	(0.0000)	(0.0001)	(0.0001)		
lag 36	0.365%***	-0.029%***	0.388%***		
	(0.0001)	(0.0001)	(0.0003)		
lag 37	-0.001%	-0.020%***	0.611%***		
	(0.0000)	(0.0000)	(0.0002)		
lag 38	-0.002%	0.019%***	1.036%***		
	(0.0000)	(0.0000)	(0.0002)		
lag 39	0.106%***	-0.010%***	1.094%***		
	(0.0000)	(0.0000)	(0.0003)		
lag 40	0.122%***	0.004%	1.731%***		
	(0.0000)	(0.0001)	(0.0003)		
lag 41	0.324%***	0.032%***	3.043%***		
	(0.0000)	(0.0001)	(0.0006)		
lag 42	0.431%***	-0.134%***	19.571%***		
	(0.0001)	(0.0005)	(0.0017)		
lag 43	0.402%***	0.005%			
	(0.0001)	(0.0001)			
lag 44	0.092%***	-0.034%**			
	(0.0000)	(0.0002)			
lag 45	1.977%***	-0.028%			
	(0.0000)	(0.0002)			
lag 46	2.168%***	-0.004%			
	(0.0001)	(0.0001)			
lag 47	1.628%***	-0.046%***			
	(0.0001)	(0.0001)			
lag 48	6.505%***	0.143%***			
	(0.0005)	(0.0003)			
lag 49	0.846%***	0.096%***			
	(0.0001)	(0.0002)			
lag 50	0.368%***	-0.014%			
	(0.0002)	(0.0002)			

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lag 51	0.569%***	-0.113%***				
	(0.0002)	(0.0003)				
lag 52	1.806%***	-0.171%***				
	(0.0001)	(0.0003)				
lag 53	1.067%***	-0.266%***				
	(0.0001)	(0.0006)				
lag 54	4.995%***	-0.535%***				
	(0.0003)	(0.0017)				
lag 55	3.980%***					
	(0.0002)					
lag 56	4.105%***					
	(0.0002)					
lag 57	4.009%***					
	(0.0003)					
lag 58	5.311%***					
	(0.0003)					
lag 59	8.435%***					
	(0.0006)					
lag 60	7.286%***					
	(0.0017)					

Note: 1. *** p<0.01, ** p<0.05, * p<0.1

2. Robust standard errors are in parentheses.

3. Lag 1 represents the first period after the city has implemented the policy, lag 2 represents the second period, and so on.

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Table 5. The overtime impact of the automobile purchase restriction policy on the market share of plug-in hybrid electric vehicles in each restricted city

	Beijing	Guiyang	Guangzhou	Tianjin	Hangzhou	Shenzhen
lag 1	0.096%***	0.023%***	-0.071%***	-0.042%***	-0.132%***	-0.302%***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
lag 2	0.509%***	0.004%	0.230%***	-0.048%***	-0.149%***	0.393%***
	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0003)
lag 3	0.009%	0.002%	0.631%***	0.126%***	1.576%***	0.159%***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)
lag 4	0.016%**	-0.017%***	0.991%***	0.153%***	18.000%***	3.736%***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0003)
lag 5	0.005%*	-0.002%	1.121%***	0.271%***	0.329%***	1.500%***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)

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lag 6	0.005%*	-0.017%***	1.025%***	0.162%***	0.514%***	1.491%***
	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0002)	(0.0004)
lag 7	0.076%***	-0.032%**	1.830%***	0.186%***	1.006%***	3.510%***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0005)
lag 8	-0.004%	-0.023%***	1.604%***	0.192%***	0.427%***	4.061%***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
lag 9	0.125%***	-0.034%***	0.955%***	0.663%***	22.785%***	6.672%***
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0007)	(0.0003)
lag 10	0.059%***	-0.023%***	1.009%***	0.732%***	0.459%***	10.007%***
	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0004)
lag 11	0.016%***	0.001%	1.176%***	0.881%***	0.197%***	11.877%***
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0006)
lag 12	0.002%	-0.023%***	1.780%***	5.405%***	1.016%***	38.164%***
	(0.0000)	(0.0000)	(0.0001)	(0.0007)	(0.0003)	(0.0020)
lag 13	-0.020%	-0.038***	1.617%***	1.161%***	0.244%***	
	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0003)	
lag 14	0.001%	-0.019%***	1.808%***	2.568%***	1.823%***	
	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	
lag 15	0.093%***	-0.012***	1.832%***	0.785%***	8.627%***	
	(0.0001)	(0.0000)	(0.0001)	(0.0003)	(0.0005)	
lag 16	0.523%***	-0.004%	1.374%***	1.444%***	17.395%***	
	(0.0000)	(0.0000)	(0.0001)	(0.0003)	(0.0005)	
lag 17	0.161%***	-0.052%***	1.468%***	1.519%***	9.624%***	
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	
lag 18	0.721%***	-0.079%***	1.132%***	1.653%***	17.042%***	
	(0.0000)	(0.0002)	(0.0001)	(0.0005)	(0.0004)	
lag 19	0.929%***	-0.046%***	1.489%***	1.423%***	5.793%***	
	(0.0001)	(0.0001)	(0.0000)	(0.0005)	(0.0004)	
lag 20	0.052%***	-0.009%	1.716%***	2.145%***	6.735%***	
	(0.0001)	(0.0001)	(0.0000)	(0.0003)	(0.0007)	
lag 21	0.127%***	-0.043%***	1.167%***	1.856%***	8.714%***	
	(0.0000)	(0.0001)	(0.0001)	(0.0004)	(0.0020)	
lag 22	0.102%***	0.022%***	1.056%***	2.943%***		
	(0.0000)	(0.0000)	(0.0001)	(0.0004)		
lag 23	0.059%***	-0.028%***	1.145%***	5.432%***		
	(0.0002)	(0.0001)	(0.0001)	(0.0007)		
lag 24	0.298%***	0.013%	7.402%***	13.209%***		
	(0.0002)	(0.0001)	(0.0010)	(0.0020)		

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lag 25	0.104%***	0.091%***	1.126%***		
	(0.0001)	(0.0000)	(0.0001)		
lag 26	0.038%***	0.076%***	1.291%***		
	(0.0001)	(0.0001)	(0.0001)		
lag 27	0.088%***	-0.018%***	1.430%***		
	(0.0001)	(0.0001)	(0.0002)		
lag 28	0.079%***	0.018%***	1.568%***		
	(0.0000)	(0.0001)	(0.0002)		
lag 29	0.087%***	0.244%***	2.192%***		
	(0.0001)	(0.0001)	(0.0002)		
lag 30	0.093%***	0.183%***	6.036%***		
	(0.0001)	(0.0001)	(0.0007)		
lag 31	0.114%***	0.025%***	6.752%***		
	(0.0000)	(0.0000)	(0.0001)		
lag 32	0.106%***	-0.009%**	2.981%***		
	(0.0001)	(0.0000)	(0.0004)		
lag 33	0.106%***	0.949%***	1.876%***		
	(0.0001)	(0.0000)	(0.0003)		
lag 34	0.068%***	-0.053%***	0.321%***		
	(0.0001)	(0.0001)	(0.0004)		
lag 35	0.132%***	0.145%***	1.136%***		
	(0.0000)	(0.0001)	(0.0003)		
lag 36	0.499%***	-0.036%***	1.921%***		
	(0.0001)	(0.0001)	(0.0005)		
lag 37	-0.023%***	0.830%***	2.089%***		
	(0.0000)	(0.0001)	(0.0005)		
lag 38	-0.029%***	0.006%	3.574%***		
	(0.0000)	(0.0001)	(0.0003)		
lag 39	0.189%***	-0.037%*	5.383%***		
	(0.0000)	(0.0002)	(0.0004)		
lag 40	0.192%***	-0.031%	5.931%***		
	(0.0001)	(0.0003)	(0.0004)		
lag 41	0.321%***	-0.003%	6.770%***		
	(0.0001)	(0.0002)	(0.0007)		
lag 42	0.463%***	0.780%***	23.129%***		
	(0.0001)	(0.0007)	(0.0020)		
lag 43	0.474%***	-0.028%**			
	(0.0001)	(0.0001)			

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lag 44	0.169%***	-0.056%			
	(0.0001)	(0.0004)			
lag 45	2.033%***	-0.079%***			
	(0.0002)	(0.0003)			
lag 46	2.245%***	-0.045%			
	(0.0003)	(0.0004)			
lag 47	1.677%***	-0.056%**			
	(0.0002)	(0.0003)			
lag 48	6.525%***	0.102%			
	(0.0007)	(0.0005)			
lag 49	0.916%***	0.197%***			
	(0.0001)	(0.0005)			
lag 50	0.369%***	-0.034%			
	(0.0004)	(0.0003)			
lag 51	0.597%***	-0.085%**			
	(0.0003)	(0.0004)			
lag 52	1.815%***	-0.105%**			
	(0.0004)	(0.0004)			
lag 53	1.113%***	-0.269%***			
	(0.0003)	(0.0007)			
lag 54	5.008%***	-0.683%***			
	(0.0005)	(0.0020)			
lag 55	4.001%***				
	(0.0005)				
lag 56	4.403%***				
	(0.0003)				
lag 57	4.233%***				
	(0.0004)				
lag 58	5.530%***				
	(0.0004)				
lag 59	8.856%***				
	(0.0007)				
lag 60	8.523%***				
	(0.0020)				

Note: 1. *** p<0.01, ** p<0.05, * p<0.1

2. Robust standard errors are in parentheses.

3. Lag 1 represents the first period after the city has implemented the policy, lag 2 represents the second period, and so on.

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5. Conclusion

This paper takes the monthly data of China's new registered vehicles from January 2011 to December 2015 to calculate the market share of BEVs and PHEVs and then adopt the DID method to carry out two parts of experimental estimation. First, use the concept of the average treatment on treated to measure the impact of the CPRP on the six restricted cities, namely Beijing, Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen in order to probe whether the policy will really stimulate the sales of NEVs. The result turns out that the market share of NEVs in the restricted cities is significantly higher than that of non-restricted cities due to the implementation of the CPRP, especially for the PHEVs sector, which infer that the CPRP do have a positive impact on the promotion of the NEVs.

Moreover, by observing the overtime changes within interaction coefficient under the DID model in those cities where the CPRP has been issued, it can be found that the effect of the CPRP was quite not obvious in the short run. But as the time of the policy be implemented longer, the increase of market share in both BEVs and PHEVs will be more and more phenomenal. It is speculated that the possible reason is because consumers may still tend to hold a wait-and-see attitude when the just policy implemented. However, as time going, consumers may descend their doubts about the performance and convenience of NEVs. In addition, with the continuous advancement of NEVs production technology, the cost of purchasing NEVs has fallen. Coupled with the benefits brought by the CPRP, as the demand of the car keep increase, the cost gap between purchasing NEVs and competing with fuel vehicles quota has been widen. As a result, consumers may become more and more incline to choose to purchase the NEVs.

For the real-world situation, in view of the success of the CPRP in promoting the development of NEVs, Hainan, the latest restricted city where implemented the CPRP in 2018, was announced to become the first province that extends the restriction policy throughout the whole province. The tricky point is that the quantity of Hainan’s car ownership at the end

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of 2017 was only about 1 million vehicles, which is far less than one-fifth of that of Beijing. That is, the purpose of implementing the CPRP in Hainan Province is no longer just only to aim to alleviate traffic congestion, but is more likely to be a policy to accelerate the development of NEVs industry.

Nonetheless, when returning to the original intention of promoting NEVs, which is to relieve the car fume problem in the city, its effectiveness has long been arguing. Some researches pointed out that simply control the number of cars may not fundamentally solve these problems. For instance, Feng et al. (2012) believe that the relationship between car ownership and car driving is not always completely correlated. Ownership is just one of the many factors that may affect overall car usage. Chen (2014) applied the indifference curve to analyze the problem of traffic congestion and came to the conclusion that the problem of congestion is lying in the excessive use of cars instead of the number of cars. Hao et al. (2010) considered that with the reduction in car ownership and the increase in the proportion of NEVs used, although it may not be able to bring immediate improvements to these problems in the short term, but may still bring great help to improve these problems in the future.

Thus, if the China government wants to achieve their prospects of improving traffic quality, energy-saving, and carbon reduction, this is still far from enough. They should still make more attempts to match diversified development measures with each other in addition to the CPRP, and adjust the policies and supports in time, so as to ensure that the quality of life may able to be improved without harming the national economy.

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