The Roles of Subsidy and Green License Policy in Putting More Electric Vehicles on the Road: Evidence from Beijing

Wen Tian *

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Abstract

In response to global climate change and environmental problems, policymakers worldwide have implemented various policies to put more electric vehicles (EVs) on the road. In this study, I evaluate the impacts of two demand-side interventions - EV subsidies and the green license plate policy (which exempts EVs from stringent vehicle license quota restrictions) on the EV market in Beijing. I develop a two-stage discrete choice model incorporating consumers' preferences for license plate types and vehicle models and estimate the demand model using product-level data with consumer-level microdata. I find that the green license plate policy is as effective as EV subsidies in promoting EV sales, and it is equivalent to approximately $7,839 subsidies in deploying EVs in Beijing, in 2015. The results also show that the green license plate policy led to increased market power of EV producers implying the critical role of government in designing the EV promotion policies.

*Ph.D. candidate, Department of Economics, the Pennsylvania State University, wkt5064@psu.edu.

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1 Introduction

Regulators view electric vehicles (EVs) as a promising solution to the environmental and energy challenges in the automobile industry (Holland, Mansur, Muller and Yates, 2016). As a result, policymakers worldwide have implemented various measures to encourage the adoption of electric vehicles as part of the emerging green industries. For example, the federal Government provides tax credit of up to $7,500 per qualifying EV for qualifying buyers starting from 2022 in the United States. In China, the local government in Beijing has introduced multiple policies and incentives to promote the use of electric vehicles (EVs) and drive the development of the EV market since 2014. These measures include not only financial incentives, such as EV subsidies, but also a special non-financial incentive, the green license plate policy. The green license plate policy grants EVs a registration privilege in Beijing, where vehicle purchases are subject to a stringent vehicle license quota system.

This paper examines the impacts of two EV promotion policies in Beijing: EV subsidies and the green license plate policy. Specifically, it addresses the following questions: How many additional EVs does each policy put on the road? How many gas cars have been replaced by EVs due to these policies? How cost-effective is each policy in deploying EVs?

To answer these questions, I need to estimate the demand for both EVs and gasoline vehicles (GVs). However, there are two challenges in our study. First, the commonly used standard discrete choice model (Berry, Levinsohn and Pakes, 1995) in the demand estimation literature does not fit our analysis because the model assumes that consumers pick their most preferred option from all available choice options (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022). In our context, the green license plate policy exempts EV consumers from a binding license quota policy. This policy requires consumers to choose from a limited set of eligible EV models. As a result, the observed sales of EVs depend not only on consumer preferences but also on the constraints of the choice sets imposed by the policy. Second, the unobserved consumer preference heterogeneity for EV models matters a lot in evaluating the effectiveness of EV policies in deploying EVs. For example, buyers who value EVs would have purchased EVs even if there was no EV promotion policies (Xing, Leard and Li, 2021).

To estimate the demand for EVs and address the above issues, I build a structural model that jointly considers consumers' preferences for license plate types and vehicle models, allowing for unobserved heterogeneity in consumer preferences for EV models. On the demand side, I develop a two-stage random coefficient discrete choice model, extending the framework of (Berry et al., 1995), and integrate policy factors for EV subsidies and license policies into consumers' vehicle model choices. Using this structural model, I estimate the demand for EVs and gasoline vehicles (GVs) and identify consumers' random tastes for EV models. This estimation leverages three data inputs: a comprehensive product-level vehicle registration dataset in China from 2010 to 2015, novel information on consumers' license plate applications, and microdata on EV consumers' stated second choices. The microdata greatly improves the precision of the random coefficient estimates and the resulting substitution patterns. Using the estimated structural model, I infer product-level marginal cost from each firm's profit maximization problem. I then conduct counterfactual simulations in which I separately eliminate subsidies and the green license plate policy in the sample period 2014 - 2015 in Beijing. This approach allows me to examine the effects of both EV promotion policies: subsidies and the green license plate policy.

Counterfactual analysis provides the following three key findings that are robust across sample cuts. First, both subsidies and the green license plate policy played crucial and comparable roles in promoting EV sales and their impacts in deploying EVs complemented each other. Counterfactuals show that there would have been a 182.2% increase in the number of EVs on the road, equivalent to 2,174 additional EVs in the sample data period (2015), Beijing had we only introduced the EV subsidies, which amounted to about 22.5% of pre-subsidy vehicle prices. Had only the green license plate policy been implemented, there would have been a 206.6% increase, equivalent to 2,465 additional EVs. Together, the combination of EV subsidies and the green license policy resulted in 7,611 more EVs on the road in Beijing in 2015.

Second, I find neither EV subsidies nor the green license plate policy led to significant substitutions between gasoline vehicles (GVs) and EVs in the sample period in Beijing. Both EV promotion policies attract inframarginal buyers who originally would not choose the outside option of no purchase. The finding contradicts the asserted objectives of these policies which aim at encouraging transitions from GVs to EVs.

Third, I find that the green license plate policy could lead to significant market power increases of EV manufacturers, especially when there is very few competitors in the market. This large impact is driven by the separation of GV and EV market under the green license plate policy in the sample data period in Beijing. These findings demonstrate the effectiveness of EV policies in putting more EVs on the road and underscore the potential role of government in designing and improving EV policies.

My paper contributes to recent studies that use demand estimation in the electric vehicle markets to evaluate demand-side EV promotion policies. The literature extensively discusses the impacts of EV subsidy programs worldwide (Chen, Hu and Knittel, 2021; Springel, 2021; Guo and Xiao, 2022). However, the effectiveness and cost-efficiency of the green license plate policy have not received sufficient attention or discussion. By examining EV demand under license policies, this work provides an innovative perspective on the policy drivers behind the rapid growth of the EV market in large Chinese cities. It also fills a gap in the literature by evaluating the impacts and interactions of subsidies and the green license plate policy in the EV market.

My findings of the substitution between gasoline cars and electric vehicles under subsidies and the green license plate policy in China complement research that discusses the transition from conventional gasoline cars to EVs under various EV policies, such as Holland et al. (2016), Holland, Mansur and Yates (2021) and Xing, Leard and Li (2021). These studies have highlighted the critical role of substitutability in designing EV policies and measuring the environmental benefits of such policies. My results provide a novel empirical perspective on for policy designs in the EV market.

My model builds on earlier literature on the discrete choice model (Berry, Levinsohn and Pakes, 1995; Petrin, 2002) and extends the framework developed in consumer choice models with choice set constraints (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022). As detailed above, I develop a two-stage discrete choice model that utilizes consumers' choices of license types to determine their choice sets. This approach generalizes the discrete choice model by relaxing the assumption that consumers consider all available options. Additionally, my approach is inspired by Gowrisankaran and Rysman (2012), assuming that consumers' valuation of license plates is based on their expected utility from potential choice sets.

This work also adds to previous studies on the Chinese vehicle license quota system

(Xiao, Zhou and Hu, 2017; Li, 2018; Zheng et al., 2021), which analyzes the mechanisms and welfare impacts of China's vehicle quota system in major cities such as Shanghai and Beijing. In contrast to these studies, my research focuses on the analysis of EV policies and the EV market.

Our research is closely related to Li et al. (2020) who use a linear regression framework to examine the policy and market drivers behind the rapid development of the electric vehicle market in China. Relative to their work, this paper builds a structural model integrating consumers' choices of license types into the demand analysis of electric vehicles, allowing us to conduct counterfactual analysis and discuss more policy implications.

The remainder of the paper is organized as follows. Section 2 provides the empirical background including policies and data. Section 3 shows the impacts of the green license policy and subsidies with a difference-in-differences setup. Section 4 describes the structural model. Section 5 discusses model estimation and the results. Section 6 present the policy analysis based on counterfactual simulations. Section 7 concludes.

2 Policy and Data Description

In this section, I first describe the policy background for EV policies in China. Then I discuss the EV policies implemented in Beijing and present our data.

2.1 Policy Background

Over the last three decades, China has experienced rapid economic growth along with significant changes in nearly every aspect of life. One of these changes is that an increasing number of people living in cities are now more willing to pay for private cars than ever before. The dramatic rise in vehicle ownership brings convenience to the public but also causes environmental and traffic issues such as traffic congestion and air pollution, especially, in large cities such as Beijing and Shanghai.

To reduce road congestion and improve air quality, seven city councils in China announced a trial program to limit vehicle usage. During 2010 - 2015, Beijing, Shanghai and other five cities [1] established a policy of capping new license restrictions. As documented by Xiao, Zhou and Hu (2017) and Li (2018), the license quota system played an important role in controlling the total number of cars on the road[2]. Among the seven cities, Beijing has adopted a non-transferable lottery system to allocate the license plates since January 2011. According to Beijing's official records, the annual quota was around 240,000 licenses during 2011 – 2013 and was reduced to 150,000 after 2013. The limited number of license quotas and increasing demand for new vehicle registration led to a decreasing low winning odds of a license plate in Beijing falling from 6% in February 2011 to an all-time low of 0.65% in 2015. As a result of the stringent quota policy, it would take years for a first-time buyer in Beijing to obtain a new license and get her car registered (Qin et al., 2021).

2.1.1 EV Promotion Policies

In addition to the efforts to limit the usage of gasoline cars, the Chinese government also affirmed its target of supporting the deployment of electric vehicles (EVs) among private car users in 2010. This is also the focus of our study. Driven by the incentives of technological upgrading, environmental sustainability, and energy security, a series of ambitious programs aiming to build a first-class EV industry have been initiated since 2010.

During 2010 - 2013, the central government of China initiated the first phase of a national cash incentive scheme for electric vehicles (EVs), offering private purchasers of eligible EVs a cash rebate ranging from 30,000 to 60,000 RMB (approximately 4,615 to 9,230 USD), with the specific subsidy amount determined by the attributes of the vehicle. Following this, a second phase of the subsidy program was rolled out in September 2013 and continued until December 2015, providing a reduced subsidy of 30,000 to 40,000 RMB (about 4,615 to 6,154 USD), again dependent on the characteristics of the vehicle.

Local Subsidy. Despite the central subsidy, local governments have also implemented their own subsidy schemes for electric vehicles (EVs). These local programs vary by city in terms of their timing and magnitude. As the focus of our study, the Beijing municipal government provided a subsidy of approximately 45,000 RMB (7,223 USD) to qualifying

[1] Hangzhou, Tianjin, Guangzhou, Shenzhen, and Guizhou

[2] Details about the license quota policy are in Appendix B

EVs beginning in 2014. The amount of local subsidy accounts for 22.5% of average EV prices in the same period.

Green License Policy. Besides the subsidy programs, the municipal government with license capping policies also made responses to the central political incentives to promote EVs. They exempted EV buyers from the stringent license quota system and offered them special EV licenses (called as green license policy in China). Since January 2014, the Beijing municipal government has established a separate license application system that offers additional license plates for electric vehicle (EVs) buyers. Under the new regulation, private purchasers of electric vehicles can directly apply for a license plate, without having to participate in the complex lottery application system for a regular license plate.

Though the EV license system also sets a quota for the number of green license plates, it was not binding. The official website of the Beijing Transportation Bureau shows the winning odds of an EV license plate was 100% in February 2014 while the winning odds of a regular license plate were 0.903% during the same period in Beijing. The green license policy in Beijing offered an easy and convenient way to obtain a license plate for potential vehicle buyers and shortened the waiting periods for a new license plate compared with the complex lottery system, which provided possibly huge incentives for EV ownership (Li et al., 2020).

Whitelist. Aside from subsidy and the green license policy, the Beijing government published its whitelist[1] of eligible electric vehicles (EVs) to distribute the subsidies and green license plates. Similar to the "whitelist" policy on battery firms documented by Barwick et al. (2024), these preferential treatments on EVs required that only eligible EVs on the whitelist could enjoy the policy benefits. In 2014, there were around 30 battery EVs (BEVs) and plug-in hybrid EVs (PHEVs) across the country. But only seven domestic battery electric vehicles (BEV) models are covered on Beijing's EV whitelist including E150EV made by BAIC Group, e6 made by BYD, Roewe E50 made by Roewe (SAIC Motor), etc. This local whitelist differs across cities. However, the whitelist policy in Beijing is considered to be very strict by the public[2] comparing with the whitelist in other cities which allows not

[1] Details in «Catalogue of Beijing Demonstration Application of New Energy Passenger Vehicle Manufacturing Enterprises and Products»

[2] Source from a report published on China Association of Automobile Manufacturers

only BEVs but also PHEVs.

Appendix A summarizes the timeline of EV-related policies from city to city. In this paper, I focus on the impacts of local subsidies and the green license policy in the context of Beijing. We also discuss the effects of removing the whitelist under these EV promotion policies.

2.1.2 China's Electric Vehicle Market

In 2010, China's EV industry was nascent, with the EV market still underdeveloped. By the end of 2010, approximately 7,100 electric vehicles had been sold across China. At that time, the market featured merely six plug-in hybrid EV models, and battery electric vehicles were notably absent.

Along with the introduction of policies aimed at promoting EVs and a political drive to advance the EV industry, annual EV sales surged significantly and reached 946,294 by the end of 2020 with hundreds of EV models. The decade saw the EV market penetration rate climb from 0.04% to 4.81%. The World Bank highlights that by 2020, China had emerged as a global leader in the EV market. By the end of 2012, approximately 186,600 passenger EVs were sold worldwide, with China accounting for 11,573, or 6.2% of these sales. By 2020, China's share had escalated to 30.5%, indicating the swift expansion of its EV market.

2.2 Data

Our analysis relies on five main data sets. The first data set we use contains the quarterly sales of vehicles at trim-level in 34 cities in China, including provincial capital cities or municipalities, over the period of 2010 – 2015. The data set comes from Chinese vehicle registration records and covers all registered vehicles produced domestically. I define each market as a city in a given quarter. Each observation in our data set represents a trim-level vehicle model in one market.

The second data set applied in our analysis is the product information data. It covers the product characteristics of all observed vehicles at the trim level. The characteristics variables include the product-level MSRP (manufacturer's suggested retail price), manufacturers, brand, model type, vehicle width, height, length, fuel consumption, segment, fuel type, and other attributes.

The third data set applied in our analysis involves policy-related information. The first part of this information is the data about license allocation in Beijing which is collected from the official website published by Beijing Municipal Commission of Transport. It includes the total quota of regular and EV license plates, the total number of applicants in the lottery application and EV license application system, the total number of applicants who choose to give up the license plates in the winner's group, winning odds of the lottery system in each quarter-year market. This data helps us identify consumer's preference for license plate types. The second part of the policy-related information is Beijing's EV whitelist collected from the website of China's Association of Automobile Manufacturers. The whitelist follows the application and admission system, and only selective battery electric vehicles (BEVs) are eligible for the beneficiary EV policies. For illustration, the most popular plug-in hybrid electric models in 2015 - Toyota Camry, Toyota Prius, and BYD Qin were not covered in Beijing's whitelist until 2018. In this data set, I summarize the models listed on the local EV whitelist and compare them with those models not approved. This data set can help us distinguish consumers' preference for beneficiary policies from preference for electric vehicle models in the structural demand estimation. The third part is the data about the amount of EV subsidies on each type of EV model and tax incentives on EV models. I include the sum of central subsidies and tax incentives into vehicle prices and summarize the amount of local subsidies and time in this data set.

The fourth data set we rely on is the market-level information. It covers the total number of population in each market and the vehicle ownership rate in each market. This data helps us define the size of the market and identify the type of vehicle consumers.

The fifth data information comes from a survey data on EV consumer's purchase intention in 2015[1]. It provides the second choice information of EV consumers defined as the percentage of consumers choosing the EV model if the current choice is not available.

[1]Data source: Big-data Analysis on EV Consumers Purchase Intention, 2015

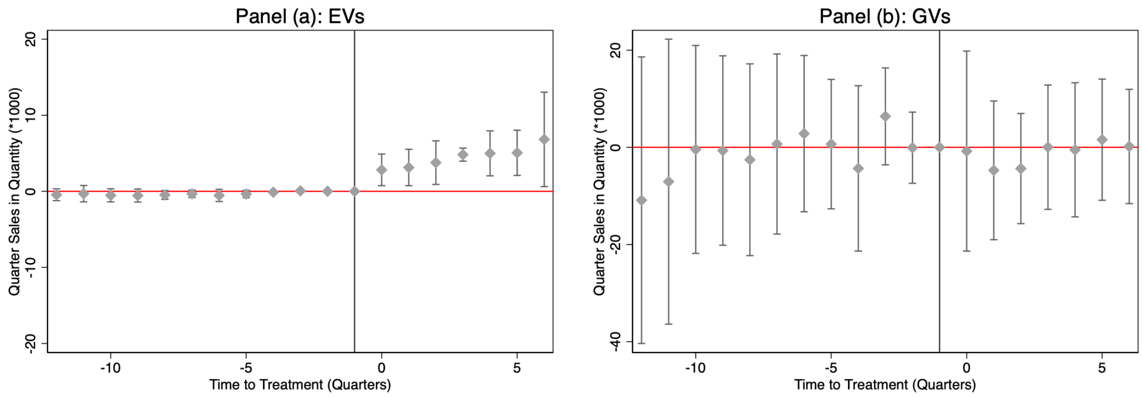
3 Effects of Subsidy and Green License Policy

I first investigate whether the green license policy leads to changes in the total sales of EVs and conventional vehicles based on an event study design. The specification is as follows:

$$Y_{gmt} = \sum_{k=-11}^{-1} a_k \cdot G_m \times T_k + \sum_{k=0}^{6} a_k \cdot G_m \times T_k + c_0 X_{gmt} + \eta_{m\times year} + \eta_t + \epsilon_{gmt}, \qquad (1)$$

where Y_{gmt} denotes the outcome measure for the group g (electric vehicles or conventional vehicles) defined as the total number of quarterly sales in city m at quarter-year t. G_m is an indicator variable which equals 1 for the treatment city (Beijing); and 0 for the control cities. T_k is an indicator variable for the k^{th} quarter-year relative to the time of the green license policy. X_{gmt} represents a vector of control variables including the subsidies, total number of quota, and total number of vehicle models in the city m at time t; $\eta_{m\times year}, \eta_t$ denotes the city-year, quarter-year fixed effects respectively. ξ_{gmt} is the error term. In the event study, the coefficients of interest are a_k, for a series of interaction terms between treatment city indicator and quarter-year dummies. The analysis extends from 11 quarters before to 6 quarters following the policy.

Figure 1: Effect of Green License Policy on Sales: Event Study



***Notes**: The figure plots the regression coefficients for the policy change and their 95 percent confidence intervals from equation 1. Effects are normalized to the end of the quarter just before the policy. Standard errors are clustered at the city level.*

Figure 1 shows the dynamic effects ($G_m \times T_k$) by plotting the estimated coefficients with 95 percent confidence intervals for the sales of EVs in Panel (a), the sales of conventional vehicles in Panel (b). We find that none of the pre-policy coefficients (a_k with $k < 0$) for

EV sales and conventional vehicle sales is statistically significant, which suggests parallel trends between the treatment and control cities before the green license policy. Following the implementation of the green license policy, there was a significant increase in the total quarterly sales of EVs and the impact persisted for at least one year and a half. During the first six quarters after the policy, the total sales of EVs increased by 4,514 on average in each quarter. The sales of conventional vehicles did not show significant changes after the green license policy.

In addition to equation 1, I also examine the impacts of subsidy on the sales using the following diff-in-diffs framework:

$$Y_{gmt} = b_1 \cdot G_{mt} + b_2 \cdot D_{mt} + c_0 X_{gmt} + \eta_m + \eta_t + \epsilon_{gmt}, \tag{2}$$

where Y_{gmt} is the logarithm outcome measure of sales for the group g (EVs and conventional vehicles) in the city m during month-year t. G_{mt} is an interaction indicator for the treatment cities with the green license policy which takes the value 1 if the policy city m implemented the green license policy during and after month-year t and 0 otherwise. D_{mt} is the interaction indicator for the treatment cities with the central or local subsidies which is equal to 1 if the policy city m starts the central or local subsidy program during and after month-year t and 0 otherwise. X_{gmt} is a vector of control variables including indicators for license quota policies and tax incentives and a constant. We also include city and month-year fixed effects in the regression through the terms η_m and η_t. The coefficients b_1 and b_2 capture the impacts of the green license policy and subsidies on the sales of EVs and conventional vehicles in the DID approach. The larger the coefficient b_1, b_2, the stronger the impacts of the relevant policies on the sales of EVs. Here, $(e^{b_1} - 1)$ and $(e^{b_2} - 1)$ provide the percentage change observed after the green license policy and the subsidies implemented holding all other variables controlled.

Following the specification in equation 2, I obtained the regression results in Table 1. Here, the first two specifications differ in the definition of EVs: the first specification (1) uses all the EVs, while the second specification (2) includes only the EV models that are qualified for the EV policies (named as listed EVs). The third specification focuses on the sales of conventional vehicles, instead of EVs, in the first two specifications. In terms of independent variables, the first regressor is an estimate of b_1 and depicts the percentage increase in sales after the local government declared the green license policy to the public,

Table 1: DID Regression Result

Quantitative Effects	(1)		(2)		(3)	
ln (No. of sales)	All EVs		Listed EVs		Conventional Vehicles	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Treatment Cities × Green license policy	2.500	(0.258)	4.505	(0.266)	-0.279	(0.0676)
Treatment Cities × Central subsidy	-0.0324	(0.0801)	0.118	(0.0879)	0.0764	(0.0161)
Treatment Cities × Local subsidy	1.112	(0.113)	1.088	(0.125)	0.0274	(0.0229)
City fixed effect	YES		YES		YES	
Month-Year fixed effect	YES		YES		YES	

***Note**: The table displays the regression coefficients and standard errors for the policy changes based on equation 2. The data includes 34 cities in 72 months during 2010-2015. Specification (1) uses the total monthly sales of all EVs as the outcome measure. In Specification (2), I only include the sales of EVs qualified for the EV policies (named as listed EVs) for the outcome measure. Specification (3) checks the sales of conventional vehicles.*

which is included to verify the impacts of the green license policy. The coefficient for the green license policy in our benchmark, specification (2), is 4.505 which suggests that sales of listed EVs increased by 89.468-fold after the government announced a green license policy with all other variables controlled. The coefficients for the central and local subsidies in specification (2) suggest that total monthly sales of listed EVs increased by 12.52% and 1.74-fold after the central and local subsidies were implemented, respectively. The magnitude of the coefficients b_1 and b_2 demonstrates the substantially positive impact of the green license policy on the sales of listed EVs. These impacts are significantly large but reasonable. For example, the average monthly sales of EVs in Beijing before the policy was implemented was about 7, while that after was 537. One concern regarding the robustness of the results is the issue of externalities. The construction of charging piles may bring about positive network effects to the development of the EV market. However, this issue is not considered a problem in our results since 1) we control for city and time-fixed effects, which could capture possible externalities; 2) in the sample data period, home charging is the main method of charging EVs.

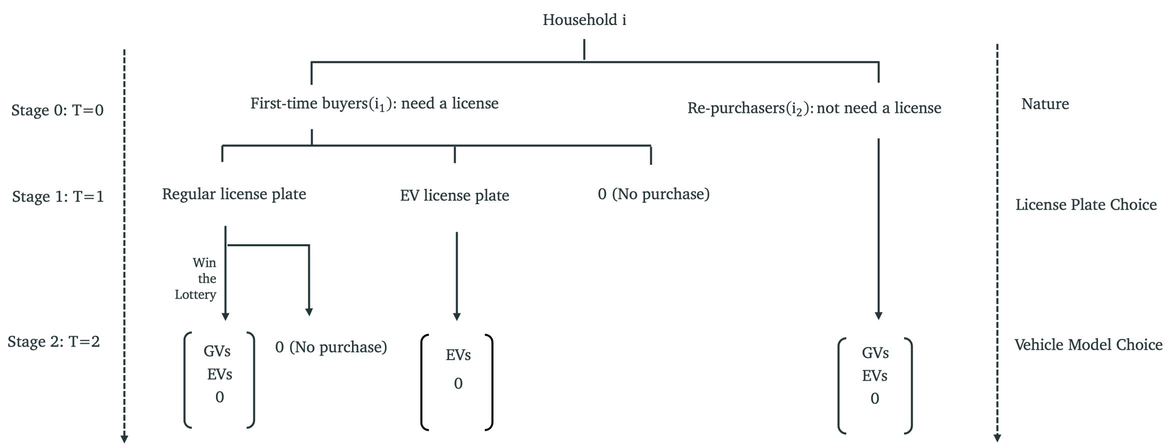
4 Structural Model

In this section, I present the structural model following the BLP (Berry, Levinsohn and Pakes, 1995) framework to separate the impacts of subsidies and the green license policy in consumers' decision process.

Our empirical model includes both demand and supply sides. On the demand side, I apply a two-stage discrete choice model to describe consumers' choices of license type and purchase behaviors in the vehicle market; on the supply side, I assume that multiproduct firms, taking product choices as given, engage in price competition following Berry (1994) and Guo and Xiao (2022). This structural model is necessary for our cost-effectiveness analysis of both policies.

4.1 Consumers

Figure 2: Model Timeline



The timing of the model on the demand side is displayed in Figure 2. At the **stage 0** ($T = 0$), consumers from the population are split into two groups - first-time buyers (denoted as i_1) and re-purchasers (denoted as i_2) by the nature. A first-time buyer i_1 does not own a license plate, and need to go through the stage 1 process to apply for a license plate under the quota system before she purchases a car in the stage 2. For a re-purchaser i_2, she has a license plate when the quota system is implemented. Thus, she does not need to get another license plate nor will she go through the choice in the stage 1. She could make her choice of vehicle models in the stage 2 with the full choice set given as $\{0, \mathcal{J}_{GV}, \mathcal{J}_{EV}\}$ where

$\mathcal{J}_{GV}$ represents the set of all available conventional vehicles. $\mathcal{J}_{EV}$ is the set of all available EVs. 0 denotes the outside option of no purchase.

At the **stage 1** ($T = 1$), the first-time buyer i_1 who does not own a license plate will go through the license application and quota process while the re-purchaser (i_2) owns a regular license plate l_r and thus does not participate the license application process in this stage. With the green license policy, the first-time buyer has three choices in the stage - participating in the regular license lottery pool or apply for a green license plate (EV license plate). Given her choice of regular license plate and conditional on winning the lottery through the quota system, she could choose from the full choice set given by $\{0, \mathcal{J}_{GV}, \mathcal{J}_{EV}\}$. If she chooses a regular license plate but lose the lottery, she cannot purchase a car without the license plate. If she applies for a EV license plate, she could get a green license plate associated with a constrained choice set of vehicle models given by $\{0, \mathcal{J}_{EV}\}$. In this stage, we assume consumers preference shocks for specific vehicle models are not realized. As a result, consumers choose which license to apply under the quota system based on the expected utility of all products available in the choice set, which are determined by a set of vehicle models that they can purchase not by a specific product. This assumption, though non-trivial, is not as restrictive as it appears. It is consistent with the common purchase behavior that consumers choose among a group of car models (e.g. EVs) before they choose a specific vehicle model[1].

At the **stage 2** ($T = 2$), the lottery results of regular license plate application are revealed to the first-time buyers i_1. Meanwhile, the product-specific preference shocks are realized. Then both groups of consumers purchase their most preferred car model j given their choice set.

In our two-stage discrete choice model, the quota system and green license policy affect buyers' choices for vehicle models through the license type choice process. It is important to mention that this two-stage model setup relies heavily on the assumption that households choose license types based on the expected utility derived from all available products in the choice set, rather than the preference for a specific product. This assumption

[1]To facilitate the identification, we also implicitly assume 1) **no dynamics**; consumers go through the model process in each market with no memory of the past choices; 2) **opportunity cost;** consumers cannot re-apply once she gets a regular or EV license plate; 3) **no resale;** consumers cannot trade their license plate.

is critical in forming this decision problem as a two-stage decision problem. Otherwise, households have to make joint decisions on their license type choice and car model choice, which makes the dimension of decision space to be too high to be tractable. Our two-stage discrete choice model takes the spirit of Abaluck and Adams-Prassl (2021) by generalizing the discrete choice model with the probabilities of consideration set.

Stage 0 - License Ownership

Stage 0 depicts the nature of the market. At this stage, we have L_{mt} potential consumers in the market m at time t which are divided into two groups of individuals - first-time buyers i_1 and re-purchasers i_2.

A first-time buyer i_1 does not have a car nor a license plate when the policy is implemented. She needs to acquire a new license plate to register a new vehicle.

A re-purchaser i_2 owns a car and does not need to acquire a new license plate when the quota policy is implemented. Under the quota policy, she can scrap her used vehicle and use the old license to register a new vehicle if she wants a new car.

The two groups of consumers cannot be distinguished because we do not observe the individual-level data and therefore do not observe the type of households in this regard. Refer to the idea of Li (2018), we assume the vehicle ownership rate across the city m at time t (denoted as o_{mt}) equals the probability of being a re-purchaser in the market m at quarter-year time t. Thus, the probability of being a first-time buyer in the market m at quarter-year time t equals $1 - o_{mt}$. The assumption may sound restrictive, but it is not too far from the reality because the quota policy implementation in Beijing is an exogenous shock to the consumers.

Stage 1 - Choice for License Types

Stage 1 models consumers' choices of license type to capture how the quota system and green license policy work. At stage 1 ($T = 1$), we assume a first-time buyer (i_1) decides between - participating in the regular license lottery, applying for an EV license plate, and staying outside. We denote i_1's choice of license types as $l \in \{l_r, l_e, 0\}$ where l_r refers to a regular license plate; l_e represents an EV(green) license plate and 0 is the outside option meaning no purchase. As required by the green license policy, the choice of license type in stage 1 constraints the consumer's choice set of vehicle models in stage 2. Especially, if the consumer i_1 chooses the EV license plate (l_e) in stage 1, then her choice set of vehicle models in stage 2 should be limited to only EV models. The relationship between choices in stage 1 (l_{i_1})and choice sets ($\Omega_{l_{i_1}}$) in stage 2 can be written as:

$$
\begin{aligned}
&i_1 \text{ chooses regular license} && \Longleftrightarrow\ l_{i_1} = l_r \ \Longleftrightarrow && \Omega_{l_r} = \{0, \mathcal{J}_{\text{gas}}, \mathcal{J}_{\text{EV}}\}, \\
&i_1 \text{ chooses EV license} && \Longleftrightarrow\ l_{i_1} = l_e \ \Longleftrightarrow && \Omega_{l_e} = \{0, \mathcal{J}_{\text{EV}}\}.
\end{aligned} \tag{3}
$$

The utility for a first-time consumer i_1 choosing the license type l ($l \in \{l_r, l_e, 0\}$) in market m at time t is given by:

$$
U_{i_1 lmt} = \underbrace{E_{mt}[V_{i_1 lmt}] - c_l}_{\overline{U}_{i_1 lmt}} + \epsilon_{i_1 lmt}, \tag{4}
$$

where $E_t[\cdot]$ denote the expected utility from getting the license plate l in market m at time t; $V_{i_1 lmt}$ is the value of obtaining the license plate of type l in market m at time t; c_{lm} is the cost of getting type l license in market m. The cost is observed by the consumers but not the econometricians. It can be interpreted as the financial or opportunity cost of participating in the complex application procedure. The identification of policy-related cost parameters comes from variations in observed consumers' choice probability for each license type in the policy city m at time t. $\epsilon_{i_1 lmt}$ denotes the random taste shock for the consumer i_1 choosing license type l in market m at time t. The utility for i_1 consumer not participating in the license lottery process is normalized to be $U_{i_1 0mt} = 0$.

To capture the idea that the valuation of each license plate choice is associated with consumers' corresponding choice set of vehicles products and facilitate our estimation, I follow the idea of Gowrisankaran and Rysman (2012) using the logit inclusive value to specify the value $V_{i_1 lmt}$ of first-time consumer i_1 obtaining the license plate of type l in market m at time t. It is written as:

$$
V_{i_1 lmt} = \ln\left[\sum_{j \in \Omega_l} \exp(\delta_{jmt} + \mu_{i_1 jmt})\right], \tag{5}
$$

where $V_{i_1 lmt}$ is the logit inclusive value denoting the ex ante value of choosing the preferred license type l as opposed to holding the outside option. Ω_l is the set of all vehicle models in the consideration group conditional on the license choice l. The relationship between the license type choice l and the choice set Ω_l is depicted in equation (3). δ_{jmt} denotes the deterministic component of a consumer's indirect utility for product j in the market m m at time t. $\mu_{i_1 jmt}$ denotes the consumer i_1's heterogeneous taste for the product j in market m at time t. Given the time of occurrence in the model, a consumer makes their license choice before their idiosyncratic taste for vehicle models is realized. Therefore, she chooses her preferred option based on the logit inclusive values of the given choice group.

There are three major advantages of taking the logit inclusive values as the value for the license type l for first-time buyers i_1 in each market. First, we simplify the decision process of license type choices to be the trade-offs between expected valuation of the relevant choice set and expected cost of applying for the type l license; 2) the individual-specific utility specification $\mu_{i_1 jmt}$ in the random coefficient demand model allows us to address endogenous selection issues in the model. The idea is that consumers with higher unobserved preference for EV models will be more likely to choose EV licenses and thus should be self-selected to participate the license application process. In our model setup, consumers unobserved taste for EVs enters the individual random taste $\mu_{i_1 lmt}$ and thus help us deal with endogenous selection issues in the model; 3) the logit inclusive value of each license-related choice set $V_{i_1 lmt}$ can be identified from the preference parameters in the stage 2.

Then, I specify the expected functional form $E_{mt}[.]$ as:

$$E_{mt}[V_{i_1 lmt}] = \underbrace{\hat{\rho}_{lmt}}_{\text{expected winning odds of license } l} \times \underbrace{V_{i_1 lmt}}_{\text{value of the license } l}, \tag{6}$$

where $\hat{\rho}_{lmt}$ is the expected winning odds of the license type l in the market m at time t defined as

$$\hat{\rho}_{lmt} = \min\left\{\frac{q_{lmt-1}}{Q_{lmt-1}}, 1\right\}. \tag{7}$$

In the equation (7), q_{lmt-1} is the total quota number for license type l set by the policymakers in the market m in the last period $t-1$. Q_{lmt-1} is the total number for applicants in the market m in the last period $t-1$. The expected winning odds of license type l equals to 1 if the quota system is not binding, e.g. EV license quota system. It equals to $\frac{q_{lmt-1}}{Q_{lmt-1}}$ if the quota system is binding.[1] The embedded assumption is that all participants have full information

[1] I use this setup as it may capture unexpected policy change in EV lottery. E.g. Beijing unexpectedly

for the quota system in the previous model period and have a rational guess of the winning odds. We assume there is no unobserved shock to individual guess of the winning odds and his participation does not affect the lottery result.

Stage 2 - Choices of Vehicle Models

To model consumers demand for vehicles, I follow the framework of discrete choice models in Berry, Levinsohn and Pakes (1995) and Grigolon and Verboven (2014).

Let the indirect utility of consumer i_k $(k = 1, 2)$ for the trim-level product j in market m and at year-quarter time t be

$$u_{i_k jmt} = \underbrace{\delta_{jmt} + \mu_{i_k jmt}}_{\bar{u}_{i_k jmt}} + \epsilon_{i_k jmt} \tag{8}$$

where i_k represents first-time buyer and re-purchaser if $k = 1, 2$, respectively. δ_{jmt} denotes the deterministic component of a consumer's indirect utility for product j in the market m m at time t. $\mu_{i_k jmt}$ denotes the consumer i_k's heterogeneous taste for the product j in market m at time t. $\bar{u}_{i_k jmt}$ represents the sum of mean utility term and heterogeneous utility term. $\epsilon_{i_k jmt}$ is an idiosyncratic consumer-vehicle specific term which follows type I extreme value distribution.

We assume the utility of a first-time buyer i_1 holding the outside option differs with that of a re-purchaser i_2 at a constant γ_1 after the implementation of the quota policy.[1] It is represented as

$$\bar{u}_{i_k 0mt} = \begin{cases} \gamma_1 & \text{if} \quad k = 1, \\ 0 & \text{if} \quad k = 2. \end{cases} \tag{9}$$

Here, γ_1 reflects factors that differ the utility of first-time buyers $(k = 1)$ and re-purchasers $(k = 2)$ choosing the outside option after the implementation of the quota policy, including

announced free EV license plates to all EV license applicants in the EV lottery in 2015-10-25.

[1]We implicitly assume that both first-time buyers and re-purchasers have the same preference parameters except the value of outside option. One may concern the validity of this assumption because the two groups of consumers may differ in income distribution or taste distribution given their previous vehicle ownership status. To identify these taste difference requires individual-level information that is not covered by our data.

the cost of re-application for license plates. We identify the parameter γ_1 from the variations between predicted shares of outside options among the license winners and the observed data of outside choices among the license winners.

We further specify the mean utility function for the consumers to consume the product j in the market m at time t as

$$\delta_{jmt} = x_{jmt}\beta + \bar{\alpha}(p_{jmt} - d_{jmt}) + \bar{\kappa}I_{j\in\mathcal{J}_{\text{EV}}} + \eta_m + \eta_t + \xi_{\text{make}} + e_{jmt}, \tag{10}$$

where x_{jmt} is the vector of observed product characteristics including vehicle length, weight, width and power; $(p_{jmt} - s_{jmt})$ is the subsidized price consumers paid for product j in market m at time t. p_{jmt} indicates the label price adjusted by tax for product j in the market m at time t. d_{jmt} is the total amount of subsidy rebate for the product j in the market m at time t offered by the government. In our setup, the prices consumers paid is the label price adjusted by tax minus subsidy rebate if applicable. $I_{j\in\mathcal{J}_{\text{EV}}}$ is an indicator which equals to 1 if $j \in \mathcal{J}_{\text{EV}}$ and 0 otherwise. η_m is the city-specific preferences for vehicles. η_t captures time (yeas-quarter) fixed effects that control for common demand shocks and seasonality across cities. ξ_{make} is unobserved make-level product attributes such as quality and safety features that do not vary over time and across markets. e_{jmt} is the unobserved time-varying and city-specific demand shocks.

I model consumer heterogeneity by interacting unobserved preferences with the EV attribute and prices. Our specifications for preferences are the following:

$$\mu_{i_k jmt} = \sigma_{EV}\nu^{EV}_{i_k mt}I_{j\in\mathcal{J}_{\text{EV}}}, \tag{11}$$

where $\nu^{EV}_{i_k mt}$ captures the unobserved consumer taste for the EV characteristic. As Allowing for unobserved heterogeneity allows for more flexible substitution patterns. Unobserved taste for EV characteristic, $\nu^{EV}_{i_k mt}$ is assumed to be independent draws from the standard normal distribution.

Note that license type choice in stage 1 constraints consumer's vehicle model choice in stage 2, the utility maximization problem for consumers differs across consumer's type and the license plates they obtained. Given that $\epsilon_{i_k jmt}$ follows the identical and independent Type I distribution, the choice probability of product j conditioning on the consumer i_k being a first-time buyer ($k = 1$) or a re-purchaser ($k = 2$) who wins a regular license plate is:

$$\mathscr{s}_{i_k jmt}(\delta, \mu | i_1, \text{win the regular license}) = \frac{\exp(\delta_{jmt} + \mu_{i_1 jmt})}{\sum_{j \in \{0, \mathcal{J}_{gas}, \mathcal{J}_{\mathrm{EV}}\}} \exp(\delta_{jmt} + \mu_{i_1 jmt})}; \tag{12}$$

$$\mathscr{s}_{i_k jmt}(\delta, \mu | i_2) = \frac{\exp(\delta_{jmt} + \mu_{i_2 jmt})}{\sum_{j \in \{0, \mathcal{J}_{gas}, \mathcal{J}_{\mathrm{EV}}\}} \exp(\delta_{jmt} + \mu_{i_2 jmt})}. \tag{13}$$

Under the green license policy, the choice probability of product j conditioning on the consumer i_k being a first-time buyer who gets a EV license through the license application process is:

$$\mathscr{s}_{i_k jmt}(\delta, \mu | i_1, \text{win the EV license}) = \begin{cases} 0 & \text{if} \quad j \in \mathcal{J}_{gas} \\ \frac{\exp(\delta_{jmt} + \mu_{i_1 jmt})}{\sum_{j \in \{0, \mathcal{J}_{\mathrm{EV}}\}} \exp(\delta_{jmt} + \mu_{i_1 jmt})} & \text{if} \quad j \in \mathcal{J}_{\mathrm{EV}} \end{cases} \tag{14}$$

As first-time buyers choose vehicle models after their license application and the lottery results revealed, our setup allows consumers with strong preference for EVs to be self-selected into EV license application process. That is, the distribution of heterogeneous taste for first-time consumers $\mu_{i_1 jmt}$ is different from that of re-purchasers $\mu_{i_2 jmt}$.

Aggregate Market Shares

I calculate the unconditional choice probability of each model j and then integrate the choice probability of each model j for each consumer over the distribution of consumers type, their license choices and the lottery results to derive the market shares of each vehicle product j in market m at year-quarter time t.

In market m at time t where the license quota policy is not implemented (named as pre-policy scenario), the market share $s_{jmt|\mathbf{pre}}$ of model j (where $j \in \{0, \mathcal{J}_{gas}, \mathcal{J}_{EV}\}$ is written as

$$s_{jmt|\mathbf{pre}} = \int \mathscr{s}_{i_k jmt}(\delta, \mu | i_k) dF(\mu_{i_k mt}, i_k). \tag{15}$$

In market m at time t where the license quota and green license policies are implemented (named as post-policy scenario), the market share of a product j in the GV group

($j \in \{\mathcal{J}_{gas}\}$) is

$$
\begin{aligned}
s_{jmt|j\in\mathcal{J}_{gas},\,\textbf{post}} &= \int \mathfrak{s}_{i_k jmt}(\delta,\mu)dF(\mu_{i_k mt}, i_k, \rho_{lmt}, l_{i_k mt}) \\
= \quad & \int \underbrace{\mathfrak{s}_{i_1 jmt}(\delta,\mu|i_1, \text{win the regular license}) \cdot \rho_{l_r mt} \cdot Pr(l_{i_1 mt} = l_r) \cdot Pr(i_k = i_1)}_{\text{choosing probability of first-time buyers } i_1 \text{ who win the regular license plate}} dF(\mu_{i_1 jmt}) \\
+ \quad & \int \underbrace{\mathfrak{s}_{i_2 jmt}(\delta,\mu|i_2) \cdot Pr(i_k = i_2)}_{\text{choosing probability of re-purchasers } i_2} \; dF(\mu_{i_2 jmt}),
\end{aligned}
\tag{16}
$$

where $\rho_{l_r mt}$ is the winning odds of a regular license type l_r in market m at time t. Under the license quota policy, the winning odds of a regular license type $\rho_{l_r mt}$ is defined as $\frac{q_{l_r mt}}{Q_{l_r mt}}$ where $q_{l_r mt}$ is the quota number set by the policymaker; $Q_{l_r mt}$ is the total number of applicants for the regular license in market m at time t. $Pr(l_{i_1 mt} = l_r)$ is the probability of a first-time buyer i_1 applying for a regular license given by the choices in Stage 1. $Pr(i_k = i_1)$ and $Pr(i_k = i_2)$ is the probability of being a first-time buyer or re-purchaser, respectively.

In the post-policy scenario, the market share of a product j in the EV group ($j \in \mathcal{J}_{EV}$) in market m at time t is

$$
\begin{aligned}
s_{jmt|j\in\mathcal{J}_{EV},\textbf{post}} &= \int \mathfrak{s}_{i_k jmt}(\delta,\mu)dF(\mu_{i_k mt}, i_k, \rho_{mt}, l_{i_k mt})dF(\mu_{i_k mt}, i_k, \rho_{lmt}, l_{i_k mt}) \\
= \quad & \int \Big[\underbrace{\mathfrak{s}_{i_1 jmt}(\delta,\mu|i_1, \text{win the regular license}) \cdot \rho_{l_r mt} \cdot Pr(l_{i_1 mt} = l_r) \cdot Pr(i_k = i_1)}_{\text{choosing probability of first-time buyers } i_1 \text{ who win the regular license plate}} \\
+ \quad & \underbrace{\mathfrak{s}_{i_1 jmt}(\delta,\mu|i_1, \text{win the EV license}) \cdot \rho_{l_e mt} \cdot Pr(l_{i_1 mt} = l_e) \cdot Pr(i_k = i_1)}_{\text{choosing probability of first-time buyers } i_1 \text{ who win the EV license plate}} \Big] dF(\mu_{i_1 jmt}) \\
+ \quad & \int \underbrace{\mathfrak{s}_{i_2 jmt}(\delta,\mu|i_2) \cdot Pr(i_k = i_2)}_{\text{choosing probability of re-purchasers } i_2} \; dF(\mu_{i_2 jmt}),
\end{aligned}
\tag{17}
$$

where $\rho_{l_e mt}$ is the winning odds of a EV license type l_e in market m at time t. Under the green license policy, $\rho_{l_e mt}$ equals to 1. $Pr(l_{i_1 mt} = l_e)$ is the probability of a first-time buyer i_1 choosing to apply for an EV license in Stage 1.

The market share of outside option is in Appendix D. Our model specification incorporates the impacts of license quota policy through the quota number q_{lmt} and the winning odds of regular license ρ_{l_r}. We integrate the green license policy through allowing the EV license choice with the winning odds ρ_{l_e} to be 100%. Consumers' responses to the license policies are depicted in the license choice process in Stage 1. Besides, we have $\bar{\alpha}$ reflecting consumers' preference for vehicle prices and subsidies.

4.2 Firms

On the supply side, we assume auto manufacturers indexed by f compete on price in a static, full information game. Manufactures simultaneously choose the price for all the vehicle models of their firms $\mathcal{J}_{mt}^{f}$ to maximize total profits in market m at year-quarter t. I assume a constant marginal cost, mc_{jmt}, associated with producing a vehicle in each market m at time t. The profit maximization problem of the firm f is given by,

$$\max_{\{p_{jmt}\}_{j\in J_{mt}^{f}}} \pi_{fmt} = \sum_{j\in\mathcal{J}_{mt}^{f}} (p_{jmt} - mc_{jmt}) s_{jmt} M_{mt}, \tag{18}$$

where p_{jmt} is the price of product j in market m at time t. J_{mt}^{f} is the set of all vehicles products of the manufacturer f. mc_{jmt} is the marginal cost of product j in market m at time t. M_{mt} is the size of market m at time t. s_{jmt} is the aggregate market share as a function of price $\mathbf{p}_{mt}$ and other factors.

The pricing first-order condition is :

$$s_{jmt} + \sum_{k,k\in J_{mt}^{f}} (p_{kmt} - mc_{kmt}) \frac{\partial s_{kmt}}{\partial p_{jmt}} = 0. \tag{19}$$

Rearranging the first-order conditions, we can solve for the marginal cost for each product with the following equations:

$$(\mathbf{p}_{mt}^{*} - \mathbf{mc}_{mt}) = -[\frac{\Delta s_{mt}}{\Delta \mathbf{p}_{mt}}]^{-1} s_{mt}. \tag{20}$$

The partial derivative matrix $\frac{\Delta s_{mt}}{\Delta \mathbf{p}_{mt}}$ for the element $\{j, k\}$ is defined as $\frac{\partial s_{kmt}}{\partial p_{jmt}}$ if products j and k are produced by the same manufacturer f and 0 otherwise. We will use marginal costs compute markups in the counterfactual analysis.

5 Estimation and Results

In this section, I discuss the identification strategy and estimation method for key parameters in the structural model and then present the estimation results.

Our goal of estimation is to recover three sets of parameters in the model. The first is the mean preference parameters δ and the mean taste for characteristics denoted as $\theta_1 = \{\bar{\alpha}, \bar{\kappa}, \beta, \eta_m, \eta_t, \xi_{\text{make}}\}$ in the mean utility equation (10). The second set of parameters is the heterogeneous taste parameter for EV characteristics σ^{EV} in the individual-specified utility equation (11) written as $\theta_2 = \{\sigma^{\text{EV}}\}$. The third includes the license application cost parameters in consumer's utility function for license types in equation (6) and the average utility of outside option for the first-time consumers γ_1 in equation (9) denoted as is $\theta_3 = \{c_{l_r}, c_{l_e}, \gamma_1\}$. I estimate the model using generalized method of moments (GMM), following the procedures outlined by Nevo (2000), Berry, Levinsohn and Pakes (2004) and Grieco, Murry and Yurukoglu (2023). Our estimation procedure is implemented in two steps. For readability, I drop the subscript $_{mt}$ from the notation for the rest of this section.

In the first step, I jointly estimate the mean consumer valuations, consumer heterogeneity and consumers' license application costs to recover the parameters $\{\delta, \theta_2, \theta_3\}$.

I compute the predicted market shares $\tilde{s}_j$ for each vehicle product in the pre-policy period and the post-policy period based on the equations in (15), (16) and (17). Referring to Berry et al. (1995) which proved that under mild regularity conditions there exists a unique vector of $\boldsymbol{\delta}$ for each market that equalizes the predicted market shares with observed market shares for given vectors of $\boldsymbol{\theta}$, and it can be recovered through the contraction mapping algorithm, I solve for $\boldsymbol{\delta}$ as a function of $\boldsymbol{\theta}$ ($= \{\theta_2, \theta_3\}$) by matching model predicted shares to the market share data through

$$\boldsymbol{\delta}^{n+1} = \boldsymbol{\delta}^{n} + \ln(\hat{\mathbf{s}}^{o}) - \ln[\tilde{\mathbf{s}}(\boldsymbol{\delta}^{n}, \boldsymbol{\theta})], \tag{21}$$

where n is the number of iterations. $\hat{\mathbf{s}}^{o}$ is a vector of observed market shares for all the products. $\tilde{\mathbf{s}}(.)$ is the function predicted market share for all the products. Then we construct the GMM estimator relying on three sets of moments as follows.

Moment 1. The first set of moments is the second-choice moments from the micro data for which we observe the shares of EV consumers who choose EVs as their second choices conditional on current choice is not available. From the model, the joint probability of consumer i_k choosing a vehicle model h in the EV group $\mathcal{J}_{EV}$ conditional on purchasing an electric vehicle model j is

$$\mathfrak{s}_{i_k(j,h)}(\boldsymbol{\theta}) = \frac{\exp\left(\delta_j(\boldsymbol{\theta}) + \mu_{i_k j}(\boldsymbol{\theta})\right)}{\sum_{g \in \mathcal{J}_{EV}} \exp\left(\delta_g(\boldsymbol{\theta}) + \mu_{i_k g}(\boldsymbol{\theta})\right)} \cdot \frac{\exp\left(\delta_h(\boldsymbol{\theta}) + \mu_{i_k h}(\boldsymbol{\theta})\right)}{\sum_{g \in \mathcal{J}_{EV} \setminus j} \exp\left(\delta_g(\boldsymbol{\theta}) + \mu_{i_k g}(\boldsymbol{\theta})\right)}.$$

I match the predicted second choice with their analogues in the micro data and construct the moments of the form:

$$g_1(\theta) = E[\widehat{1_{i_k}(h \in \mathcal{J}_{EV} \setminus j | j \in \mathcal{J}_{EV})}] - \int \sum_{j,h} \mathcal{s}_{i_k(j,h)}(\theta) dF(i_k), \tag{22}$$

where $E[\widehat{1_{i_k}(h \in \mathcal{J}_{EV} \setminus j | j \in \mathcal{J}_{EV})}]$ is the estimates of second choice in the micro data. We employ this micro moment to help with the identification of consumer heterogeneity for EVs.

Moment 2. We construct the second set of moment conditions by matching the predicted shares of outside options among the regular license winners to the observed analogues. The observed shares of outside options among the regular license winners are calculated as the number of unused license quotas in the market m at time t over the total number of quota in the market m at time t[1]. To facilitate our identification, I assume the observed number of unused quota equals the number of consumers who win the lottery of type l license application but did not buy a car model. This moment helps with the identification of the average utility of outside option among first-time buyers (γ_1). From the model, we simulate the shares of outside options conditional on first-time buyers winning the regular license type as

$$\mathcal{s}_{0|i_1,\text{win the regular license}}(\theta) = \frac{\exp(\gamma_1)}{\exp(\gamma_1) + \sum_{g \in \{\mathcal{J}_{\text{gas}}, \mathcal{J}_{\text{EV}}\}} \exp\left(\delta_g(\theta) + \mu_{i_k g}(\theta)\right)}. \tag{23}$$

Then we match the predicted shares of outside option to their empirical analogues observed in the license choice data and formulate the moment conditions as

$$g_2(\theta) = E[\widehat{\mathbf{s}^o_{0|i_1,\text{win the } l_r \text{ license}}}] - \int \mathcal{s}_{0|i_1,\text{win the regular license}}(\theta) dF(i_1), \tag{24}$$

where $E[\widehat{\mathbf{s}^o_{0|i_1,\text{win the } l_r \text{ license}}}]$ is the estimate of outside option shares among the regular license plate winners.

Moment 3. The third set of moments is formed based on the license application information from which we observe the shares of regular license applicants and EV license

[1]The lottery happens monthly or bi-monthly in Beijing. We sum up the data into quarterly numbers. Winners of regular license plats and EV license plates have an activation period (within six months in Beijing) to confirm their plate number and register their vehicle. If consumers do not register a vehicle within the period, we observe the quota number released to the lottery system and marked as unused quota.

applicants among the population. To construct the moment condition, I compute the predicted shares of choosing the regular license plates l_r and EV license plates l_e given the parameters of θ from the model in Stage 1 as

$$\tilde{\mathcal{S}}_{l|i_1}(\theta) = \int \frac{\exp\left(\hat{\rho}_l V_{i_1 l}(\theta) - c_l(\theta)\right)}{1 + \sum_{\ell \in \{l_r, l_e\}} \exp\left(\hat{\rho}_\ell V_{i_1 \ell}(\theta) - c_\ell(\theta)\right)} dF(i_1). \tag{25}$$

By matching the predicted shares to the empirical analogues of shares of regular license applicants and EV license applicants, we get

$$g_3(\theta) = E[\widehat{\mathcal{S}^o_{lmt|i_1}}] - \tilde{\mathcal{S}}_{l|i_1}(\theta), \tag{26}$$

where $E[\widehat{\mathcal{S}^o_{lmt|i_1}}]$ is the estimates for shares of each license type applicants from the observed license application data.

I stack these three sets of moments and estimate (θ_2, θ_3) via simulated GMM. We use a weight matrix based on the inverse variance matrix of the data moments. The estimation process starts with an initial guess of $(\delta^0, \theta_2^0, \theta_3^0)$, and a vector of simulated $\nu_{i_k}^{\text{EV}}$. Then we iterate the mean valuations δ through contraction mapping$\hat{\delta} = \delta(\hat{\theta}_2, \hat{\theta}_3)$ and update (θ_2, θ_3) from the outer optimization until the minimum of the GMM objective function is achieved. In the process, θ_2 is the individual-specific taste parameter which enters the utility in a nonlinear way. θ_3 includes the license type-specific application cost parameters and the average outside option value. We compute standard errors of θ_3 parameters using a bootstrap procedure. Appendix E presents the summary statistics of the observed three sets of data moments.

In the second step, I estimate the mean taste parameters for characteristics in θ_1 with the previous estimates of δ. We use our first stage estimate $\hat{\delta}$ as an estimate for δ and employ an IV regression based on the equation

$$\hat{\delta}_j = \bar{\alpha} p_j + \bar{\kappa} I_{j \in \mathcal{J}_{\text{EV}}} + x_j \beta + \eta_m + \eta_t + \xi_{\text{make}} + e_j. \tag{27}$$

Instrument Variables for prices. As addressed by the BLP literature (Berry et al., 1995), the possible correlation of vehicle prices with the unobserved demand shocks e_{jmt} suggests the potential endogeneity in vehicle prices. To establish identification for prices, I build two sets of instrument variables for prices based on the product characteristics following Bresnahan (1987) and Berry (1994). They are 1) sum of exogenous characteristics of competing products in other firms denoted as $\sum_{h,h\notin \mathcal{J}^f_{mt}} X_h$,; 2) sum of exogenous characteristics of other products produced by own firm denoted as $\sum_{h,h\neq j,h\in \mathcal{J}^f_{mt}} X_h$[1]. In the product differentiation setting assuming the observed product characteristics - vehicle width, length, power and weight are exogenous, the IVs we proposed are valid because they are correlated with prices but do not affect the unobserved demand error terms. Our identification is made possible through the assumption:

$$E[e_j(\theta_1)|\boldsymbol{Z}] = 0, \tag{28}$$

where $\boldsymbol{Z}$ include the vector of exogenous variables and instrument variables for prices.

Market Size. Given that license plate application and vehicle purchase is available to all qualified households in a market, we define the total market size in our model as the total number of households in market m at time t. This assumption of market size follows the BLP literature (Berry et al., 1995; Berry et al., 2004) by drawing consumers from the same population.

5.1 Parameter Estimates

Table 2 presents parameter estimates for our demand-side system. In the first panel, we display a subset of mean taste parameters $(\bar{\alpha}, \bar{\kappa}, \beta)$ in θ_1 and the heterogeneous taste parameter σ^{EV} for electric vehicles (EVs) in θ_2. The city, year, and make-level fixed effects are also included in the estimation but are not shown in the table. The second panel shows the policy-related parameters in θ_3 which appear as the cost of applying for regular license plates (c_{l_r}) and EV license plates (c_{l_e}) as well as the average utility of outside options among first-time buyers (γ_1).

Our estimation shows the estimate for EVs is around -6.517 indicating a strong negative preference for EV models in the sample period. It accords with the fact that consumers have range anxiety and concerns about the EV technology in the early stage of EV diffusions. In addition, we estimate a significantly large random coefficient for EVs which is around 3.849 representing substantial heterogeneity in tastes towards EV models across

[1] As we have trim-level product attributes, there are enough variations in the instrument variables even after we control for make-level product dummies ξ_{make}.

consumers. It rationalizes the strong substitution patterns observed in the second-choice data within EV groups. As a point of reference, our estimate for the EV random coefficient identified through the microdata in China in 2015 is much larger than the estimate for alternative fuel-efficient vehicles with a magnitude of 0.949 in Xing et al. (2021) using the US New Vehicle Customer Study during 2010-2014 suggesting a substantial heterogeneity in the preferences for EVs across the consumers in China in the sample period. The results in

Table 2: Parameter Estimates

Variables	Coef.	S.E.	$\hat{\sigma}$	S.E.
Parameters in θ_1 and θ_2				
Price ($\bar{\alpha}$)	-3.106	(0.234)		
EV ($\bar{\kappa}$)	-6.517	(0.249)	3.849	(0.102)
Price × Income	0.488	(0.004)		
Width	7.533	(0.348)		
Length	1.634	(0.059)		
Parameters in θ_3				
Cost of a Regular License ($\hat{c}^r$)	0.823	(0.052)		
Cost of a EV License ($\hat{c}^e$)	0.912	(0.343)		
Average Value of Outside Option ($\hat{\gamma}_1$)	-7.208	(0.281)		

Notes: *We estimate with the city dummies, year dummies and make-level fixed effects as well as the product characteristics (power, weight) that are not displayed in the table. In the first panel, we use the vehicle data from 11 Chinese cities during 2010-2015 and incorporate the micro national survey data in 2015. The total number of observations is 188,723. In the second panel, we rely on the license application information in Beijing during 2014 -2015. The total number of observations is 7,831.*

Table 2 also provide us the estimates for the license application cost and the average utility of outside options among first-time buyers. The cost parameter of applying for a regular license plate is around 0.823 while that of applying an EV license plate is 0.912. We interpret the application cost as a combination of the psychological and financial cost due to the complicated application procedures and the opportunity cost. To get a sense of the magnitude of the cost parameters, we compare the cost estimates with the price coefficient and get the monetary value of the license application cost. The results show that one-time cost of applying for a regular license quota is around 26,643 RMB ($4,277). The amount of license application cost is comparable with the license fee estimated by (Xiao et al., 2017; Li, 2018) in their studies about China's vehicle quota system. We also find that the application cost of an EV license quota is around 29,534 RMB ($4,739). It suggests higher opportunity cost associated with applying for the EV license plate as the EV license winners are not qualified to apply for a new regular license plate required by the license policies. Second, the average value of outside options among first-time buyers is negative with a magnitude of -7.208. It implies that first-time buyers have a strong disutility of choosing not to purchase after winning the regular license plate. It accords well with intuition that very few license winners would like to give up their lucky lottery and choose not to purchase a car.

The coefficient estimate for vehicle prices is around -3.106 while the interaction between vehicle prices with income is positive implying households with a higher income are less price sensitive. Given the estimates, we calculate the average own price elasticity of demand to be about -3.886. The magnitude of the price elasticity is comparable with the results in Brenkers and Verboven, 2006 and Albuquerque and Bronnenberg (2012). Using the estimates, we compute the model-to-model own- and cross-price elasticities to capture the implied substitution patterns. Table 6 in Appendix F present the sample of model-to-model price elasticities for selected brands and vehicle models. Table 6 shows that cross-price elasticities are large for cars within the EV groups implying the electric vehicle models on the list are close substitutes. Cross-price elasticities within the GV group are small due to the numerous GV products in the market. Besides, we find that cross-price elasticities across EV and GV groups are relatively small indicating small substitutability between EVs and GVs due to price changes. For example, price decrease (or a EV subsidy) of the EV model Toyota Camry (EV-version) has almost no effect on the market share of the GV product Honda Civic while the reverse is not true.

To gain a comprehensive understanding of the substitution patterns within and cross the EV and GV groups, I summarize the average model-level own and cross-price elasticities within and across the vehicle groups using the sample data of Beijing, 2014-2015 in Table 3. The mean own price elasticities of EVs and GVs are around -5.2573 and -4.3273, respectively suggesting consumers are less price-sensitive to EV models than GV models in the sample period under the license policies. The average cross-group price elasticity is about 0.0033. According to Holland et al. (2021), our estimates suggest very low cross-price elasticities between EVs and GVs (< 0.01) in the sample data period under which a ban on

Table 3: Average Own and Group-Level Cross Price Elasticities

	Own-Price Elasticities	Cross-Price Elasticities	
Group		Within-Group	Cross-Group
GV	-5.2572	1.5269	0.0534
EV	-4.3403	3.3555	0.0080

Notes: *I calculate the average group-level cross price elasticities by averaging the sum of cross-price elasticities in the group (EVs or GVs) across trim-level products using the sample data in Beijing, 2014-2015. We define the average group-level cross-price elasticities (e.g. across the group EV and GV) as the average quantity change of a typical product in the GV group, led by a one percent price change of all the products in the EV group.*

gasoline vehicles (or a non-tradable GV quota) may lead to large deadweight loss. Furthermore, the cross-price elasticities between EVs are about 0.482 indicating electric vehicles are close substitutes to each other in the sample period.

We have important implications from the estimation results. First, consumers' preference towards EV models exhibit large heterogeneity implying huge heterogeneous impacts of EV policies on the consumers. Second, electric vehicle models were close substitutes to each other in the same group, but they were inferior substitutes of GVs in the sample period.

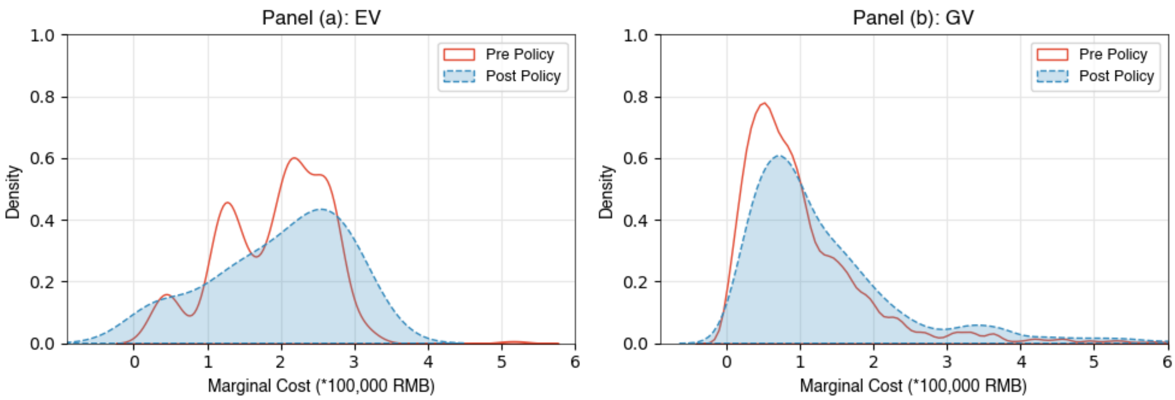
5.2 Model Fit

Table 7 in Appendix G presents the correlations between moments we target and our estimates to show the model fit. In Table 7, I summarize the second choice moment from the microdata and the average outside option shares, the shares of regular license applicants and EV license applicants from Beijing license application data set and show the fitness of our model to the three sets of moment conditions. Not surprisingly, our model estimates with micro moments is able to match the data well.

5.3 Marginal Cost Estimates

Based on the demand estimates, I compute the marginal cost c_j of each vehicle model j using equation 20. Figure 3 shows the distribution of estimated marginal cost. The average marginal cost of EVs in the full sample is 190,172 RMB ($30,525) while the average estimated marginal cost of GVs is 106,716 RMB ($17,129). It accords with the intuition that the production of EVs is more costly that GVs in the early stage when the electric vehicle industry is under development. Also, we find that the pre-policy and post-policy marginal cost estimates in EVs did not show much difference implying the underlying assumption in our analysis that EV production technology did not improve much in the sample period.

Figure 3: Marginal Cost Distribution



***Notes**: The figure plots the estimated marginal cost distribution of EV and GV models. I draw the Pre -Policy distribution based on the full sample data set excluding the policy implementation period (Beijing, 2014-2015). The Post-Policy distribution is drawn from the sample data (Beijing, 2014-2015).*

6 Policy Analysis

In this section, I first examine the role of subsidy and green license policy in driving the growth of EV market. Based on the model estimates, we simulate the counterfactual EV sales by removing each policy. Then I perform a policy comparison between the two EV policies. Furthermore, I evaluate the welfare impacts of license quota policy and whitelist policy interacting with the EV promotion policies in the automobile market.

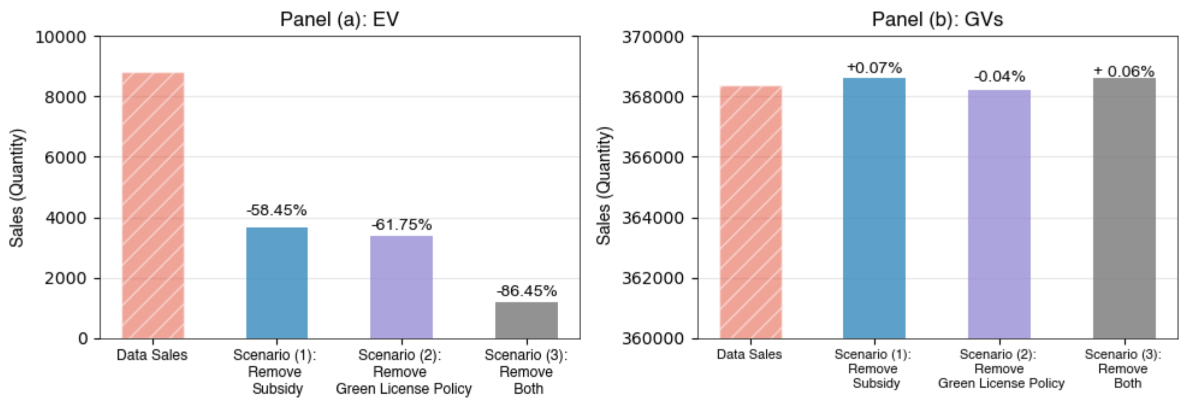
6.1 Impacts of Subsidy and the Green License Policy

In this part, I simulate the counterfactual vehicle sales and equilibrium prices by 1) removing local EV subsidies; 2) removing the green license policy; and 3) removing both policies in the context of Beijing, 2015. This setup of our counterfactual simulations facilitates us to analyze the equilibrium impacts of subsidies and green license policies in the EV and GV market. I discuss the counterfactual simulation results in terms of sales impacts, price impacts, and market power in the following analysis. The techniques we use to perform the counterfactual analysis is illustrated in details in Appendix H.

6.1.1 Sales Impacts

I study the equilibrium sales impact of removing subsidies and the green license policy on EVs and GVs considering firms' pricing in response to the policy changes. In the counterfactual scenario (1), I remove the subsidy policy by setting the subsidy amount in equation (10) to 0. In the counterfactual scenario (2), I remove the green license policy in the simulation case by eliminating the choice of EV license plate[1]. That is, the only way to get a vehicle is to either have or be obtaining a regular license. In the counterfactual scenario (3), I remove both subsidy and the green license policy by combining the settings in the previous two cases.

Figure 4: Counterfactual Sales Impacts



***Notes**: The figure plots the sales impacts in the 3 counterfactual simulations - 1) removing subsidies; 2) removing the green license policy; and 3) removing both policies on the EV and conventional vehicle market in the context of Beijing, 2015. The percentage changes represent the percentage of the total sales decrease/increase from the baseline sales -data case to the corresponding counterfactual scenario.*

Figure 4 presents the counterfactual EV and GV sales of these counterfactual scenarios,

[1]This is equivalent to setting the EV license quota to 0.

defined as the total number of sales changes in the EV and conventional car market. The simulation results in Panel (a) of Figure 4 show that without subsidies, the total sales of EVs in Beijing, 2015 would have decreased from $8,804$ sold to $3,658$, approximately 58.45% lower, and without the green license policy, the total sales of EVs would have decreased from $8,804$ to $3,367$, approximately 61.75% lower. It implies that both subsidies and the green license policy have a significantly large impact on promoting the sales of EVs. Our finding is consistent with the findings in Li et al. (2020) which also proves the substantial efficacy of the green license policy with a minimal cost. Moreover, we find that the sales in the data scenario is higher than the sum of sales in scenario (1) and scenario (2), suggesting that a policy combination of subsidy and the green license policy works more efficiently than the implementation of either subsidy or the green license policy holding the cost fixed. It provides an important implication for policymakers to deploy EVs that a quota policy combined with subsidies could be an optimal policy choice.

Despite the sizable impacts of promoting EVs, we find that subsidies and the green license policy have relatively small impact on the conventional vehicle market. Scenario (1) in Panel (b) in Figure 4 shows that the total sales of conventional vehicles would have increased by 0.07% which amounts to 258 vehicles without subsidies. We observe the sales change due to subsidies because there are consumers who prefer conventional cars without price subsidies in EVs. Scenario (2) in Panel (b) in Figure 4 shows that the total sales of conventional vehicles would have decreased by 0.04% which amounts to 152 vehicles without green license policy. This is because EVs producers would have strategically lowered EV prices had we removed the green license policy. In this case, consumers would switch from GVs to EVs due to price effects. Overall, the substitution between EVs and GVs due to the subsidy and the green license policy is very small because the substitutability between EVs and conventional vehicles is pretty low in the sample data period. This result is consistent with our estimation results in Section 6. First, we find a large random coefficient in the EV dummy variation indicating large heterogeneity in EV preference. It implies that consumers have a large preference variation towards EV models relative to other characteristics such as prices. That is, removing subsidy would not affect much in terms of EV consumer's preference towards EV models. Second, our estimation shows that the cross elasticities between EVs and Gas cars are small indicating that EV models and GV models are not close substitutes.

In addition to the impact of subsidy, Scenario (2) in Panel (b) in Figure 4 shows that the total sales of conventional cars would have decreased by 0.04% (equivalent to 157 cars) without the green license policy. The decline in sales of conventional vehicles is because the removal of the green license policy results in a drop in equilibrium EV prices and thus a substitution from conventional vehicles to EVs. However, the change is also small due to large preference variations for EV models.

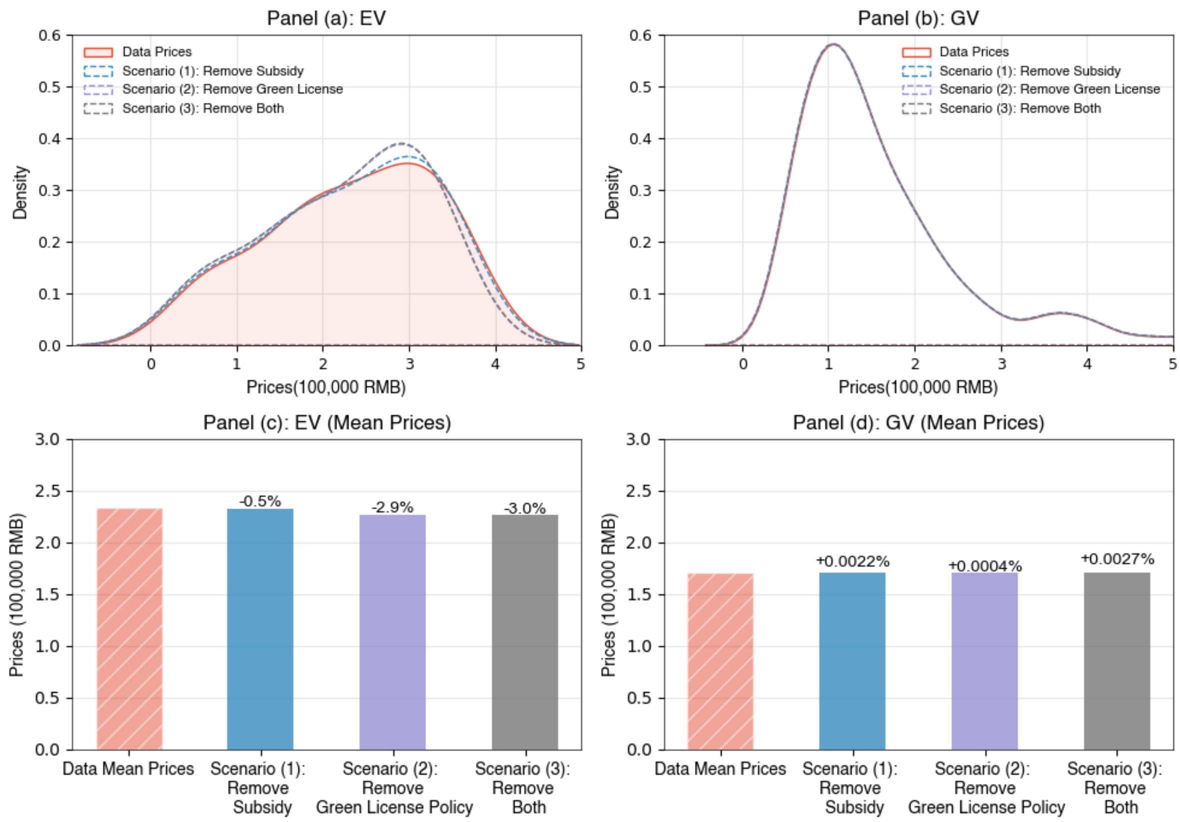
Overall, the resulting changes in the counterfactual scenarios suggest the implementation of EV subsidy or the green license policy led to little substitution from conventional cars to EVs while leading to more EV consumers from outside options in the context of Beijing, 2015. This result is consistent with the analysis of Holland et al. (2021) in the US market. As discussed by Xing, Leard and Li (2021), the substitution pattern between conventional vehicles and EVs critically determines the environmental benefits of promoting EVs. Our results imply negligible environmental gains led by both subsidy and the green license policy in the sample data period because the EV policies are not removing gas cars on the road in this early stage of EV development.

The counterfactual analysis on sales demonstrates the significant value that the green license policy can potentially provide to consumers. Also, the counterfactual analysis imply negligible environmental gains brought by the EV-related policies in the early stage of EV development due to low substitutability between EVs and GVs. Note that this conclusion does not include the environmental implications of license quota policy which aims to remove gas cars from the road. I focus on the analysis of EV-related policies in this part and discuss the environmental impacts of license quotas in the third part of our policy analysis.

6.1.2 Price Impacts

I evaluate the price impacts of subsidy policy and the green license policy on EV and GV products through the counterfactual simulations. In the analysis, we follow the counterfactual practice above and assume manufacturers in the vehicle market compete in prices to maximize their profits under the subsidy or the green license policy. The counterfactual simulations provide the equilibrium prices p^* of each vehicle model in each of the three scenarios: (1) we remove the subsidy; (2) we remove the green license policy; (3) we remove both.

Figure 5: Counterfactual Price Impacts



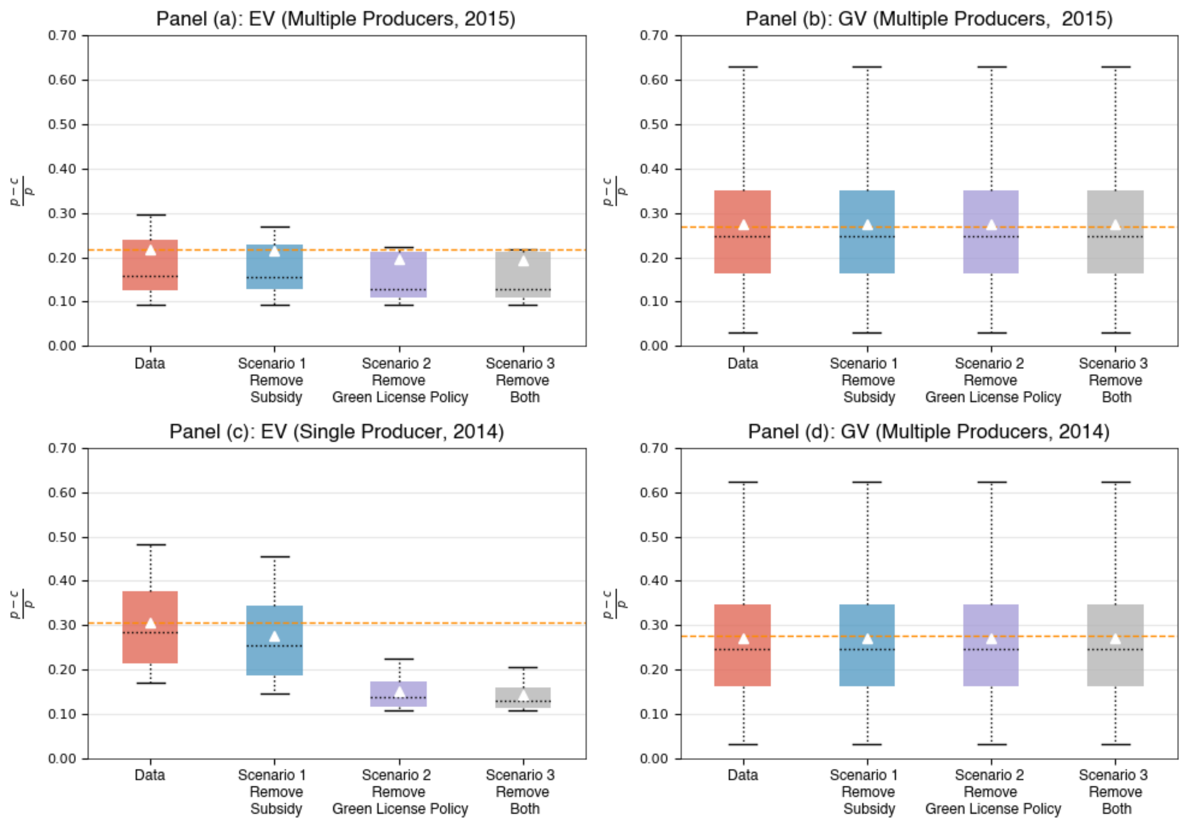
***Notes**: The figure plots the equilibrium price impacts of subsidy and the green license policy on the EV and conventional vehicle market in the context of Beijing, 2015. The simulation results come from 3 counterfactual scenarios where 1) we remove subsidies; 2) we remove the green license policy; and 3) we remove both policies. Panel (a) and (b) present the equilibrium EV and GV price distribution with the kernel density estimate plot in the data and three counterfactual scenarios. Panel (c) and (d) display the mean prices of EVs and GVs in the data and three counterfactual scenarios. The percentage changes represent the percentage of the total sales decrease/increase from the baseline sales -data case to the corresponding counterfactual scenario.*

Figure 5 presents the simulated prices in the EV and GV market. Panel (a) and (b) in Figure 5 show that removing either subsidies or the green license policy shift the EV price distributions leftward but does not have significant impacts on GV price distributions. It implies that EV manufacturers set higher prices in equilibrium in response to the implementation of subsidies and the green license policy. However, GV manufacturers did not respond much to the EV policies which is consistent with our estimation results that substitutability between EVs and GVs is relatively low in the sample data period. Panel (c) of Figure 5 shows that the mean of EV prices would have dropped by 2.9% if we removed the green license policy in Beijing, 2015. The mean of EV prices would have dropped by 0.5% had we removed the subsidies in Beijing, 2015. The results demonstrate our theoretical analysis that the green license policy could separate the EV market from the GV market and thus grant EV manufacturers larger pricing power over EV products.

To elucidate the welfare implications of subsidy and the green license policy, I first examine the pass-through of subsidy to EV producers. Referring to Kelly (2014); Pless and Van Benthem (2019), we define the pass-through rate of subsidy to producers as $\frac{p^s - p^*}{s}$. Here p^s is the product-level prices set by producers with subsidies; p^* is the unsubsidized competitive market equilibrium prices simulated through the counterfactual scenarios; s denotes the amount of subsidy. The pass-through rate usually falls between 0 and 100 percent with higher values (or lower values) indicating larger welfare benefits towards producers (or consumers). The graph interpretation and calculation of subsidy pass-through in our empirical setting is in Appendix H.1. The findings indicate that in a market with several EV producers (Beijing, 2015), the average pass-through rate at which subsidies are transferred to producers stands at approximately 1.35% in the absence of the green license policy, yet it is about 6.42% when the green license policy is implemented. Conversely, in a market dominated by a single producer (Beijing, 2014), the subsidy pass-through rate to producers is 5.74% without the green license policy, but it significantly rises to 28.42% with the green license policy in place.

Next, I calculate the Lerner indices (defined as $\frac{p_j - c_j}{p_j}$) to measure the product-level markups changes in the counterfactual scenarios. Here, p_j is the equilibrium price for each vehicle model j in each counterfactual simulation. c is the estimated marginal cost for the model j from the supply side.

Figure 6: Markups Distribution



Notes: *The figure plots the product-level markup distributions (mean, median, interquartile range, minimum and maximum) of EVs and GVs in the data case and 3 simulation scenarios where 1) we remove subsidies but keep the green license policy; 2) we remove the green license policy but keep subsidies; 3) we remove both policies. We perform the counterfactual simulations based on the sample in Beijing, 2014 - 2015. Panel (a) and Panel (b) display the markup distributions of EVs and GVs under the data and three counterfactual scenarios in Beijing, 2015 when there were multiple producers competing in both the EV and GV market. Panel (c) and Panel (d) show the markups distributions of EVs and GVs under counterfactual policy simulations in Beijing, 2014 when there was a single producer in the EV market.*

Figure 6 illustrates the markup distributions (mean, median, interquartile range, minimum and maximum) of EV and GV products in the data case and three counterfactual simulation scenarios. In Panel (a) and (b), we conduct the counterfactual simulations in the context of Beijing, 2015 when there were 6 manufacturers with 8 vehicle models competing in the EV market. The average markup (non-weighted) of EV products was 0.2189 in the data over the sample period. If we removed the subsidies but keep the green license policy in effect, the average markups would have been 0.2146. If we removed the green license policy but leave the subsidies, the average markup would have reduced to 0.1957. The average markup of GV products was around 0.2712 and did not change significantly over the counterfactual simulations. The magnitude of product-level markups is comparable with previous literature in the vehicle market (Grieco et al., 2023). In Panel (c) and (d), we simulate the counterfactual scenarios over the sample period - Beijing, 2014 when there was only a single manufacturer in the EV market. In this sample data, the average markup of EV products was 0.3052. If we removed the subsidies but kept the green license policy in effect, the markups would have been a bit lower around 0.2769. However, if we removed the green license policy, the average markups of EVs would have halved to 0.1519.

These findings on price impacts have important implications for policies aimed to deploy the electric vehicles (EVs). First, we demonstrate that EV manufacturers could potentially increase prices and secure higher profits through the adoption of subsidies or the green license policy within the EV market. To the extent that manufacturers adjust their strategies in response to these policies, the primary goal of benefiting consumers and encouraging EV adoption will be compromised. Second, our research suggests policymakers to proceed with caution regarding the implementation of the green license policy together with subsidy. This is because the green license policy markedly influences the extent to which subsidies are passed on to EV producers, despite having a considerable effect on boosting EV sales. Third, the markups reveal that green license policy significantly enhanced the market power of EV manufacturers. This underscores for policymakers the importance of taking the structure of the EV market into account when evaluating the consequences of the green license policy.

Our analysis demonstrates the effectiveness of subsidies and the green license policy in putting more EVs on the road and analyzes the impacts of both policies on equilibrium product prices.

6.2 Comparisons Between Subsidy and the Green License Policy

In this part, I conduct a policy-wise comparison between subsidy and the green license policy in terms of cost-effectiveness and welfare results.

6.2.1 Subsidies to Replace the Green License Policy

The average local subsidy for eligible EVs from Beijing government amounts to 45,000 RMB (about $7223) during our sample period (2014 - 2015). The amount is nearly 22.5% of MSRP on average. The total subsidies from the municipal government spent on EVs are nearly $63.59 million in 2015. Comparing with the huge cost of the subsidy program, the cost of introducing the green license policy under the quota system is minimal.

To quantify the cost-effectiveness of the green license policy, I calculate the amount of subsidy to replace the green license policy through a counterfactual simulation based on the data in Beijing, 2015. In the counterfactual design, we hold the total amount of EVs deployed in the data case (8,804 EVs) as the policy target. Then I simulate the amount of subsidy for each qualified EV to achieve the data sales target in the counterfactual scenario where we remove the green license policy. The results show that the government should have offered each EV additional 48,837 RMB subsidy (about $7,839) to achieve the data sales target in Beijing, 2015 if we removed the green license policy. In total, the green license policy saved the government $69.01 million in deploying the sales amount of EVs in the data.

6.2.2 Welfare Comparison

Next, I examine the welfare impacts of subsidy and the green license policy in terms of consumer surplus, producer surplus, government expenditures and externalities. Then I compare the total welfare consequences and the social policy cost of implementing each policy.

Consumer Surplus. I employ the compensating variations (CVs) to measure consumer surplus changes due to the policy implementation. I consider compensating variations (CVs) in our setting to be the additional monetary transfer required by a consumer i being offered the product bundle in a counterfactual scenario w with the outside good valued at γ_i relative to receiving only the option to purchase the hypothetical outside good γ_i. Given our model assumption, the compensation variations $\overline{CV^w}$ for an average consumer - in the w^{th} ($w = 1, 2$) scenario is given by,

$$\overline{CV^w} = \int_i \frac{1}{\bar{\alpha}} \left[\ln\Big(\sum_{j \in \{0, \mathcal{J}^w\}} \exp(\delta_j^w + \mu_{ij}^w) \Big) - \gamma_i \Big) \right] dF(i), \tag{29}$$

where $w = 0, 1, 2$ indicating the baseline scenario 0, counterfactual scenario 1 and 2. δ_j^0 is the mean utility of the product j in the baseline scenario. δ_j^w is the mean utility of the product j given the equilibrium prices in the w^{th} scenario. μ_{ij}^0 and μ_{ij}^w represents the random utility terms of each consumer i for product j including the random taste for EV products in the baseline scenario and the w^{th} scenario, respectively. In the study, I establish the baseline case (denoted as $w = 0$) as the scenario where neither EV subsidies nor the green license policy were implemented. In the counterfactual scenario 1 (denoted as $w = 1$), I simulate the case where only the green license policy are implemented. In the counterfactual scenario 2, I assume only EV subsidies are implemented. For robustness, I hold the total number of regular license quotas as fixed in the three counterfactual scenarios assuming that the green license policy only reserves license quotas for EVs. Then, the total consumer surplus $\overline{CS}$ per household in the w^{th} scenario is given by

$$\Delta\overline{CS^w} = M_w \overline{CV^w} - M_0 \overline{CV^0}. \tag{30}$$

Producer Surplus. I compute the average producers' profits changes to measure the producer surplus changes per vehicle due to EV subsidies and the green license policy. Given the equilibrium prices and sales simulated from the counterfactual scenarios 1 ($w = 1$) and 2 ($w = 1$), I calculate the average profit changes from the baseline scenario to the counterfactual scenarios. The formula of producer surplus changes is

$$\Delta\overline{PS} = \sum_j \Big[(p_j^{w*} - mc_j) q_j^{w*} \Big] - \sum_j \Big[(p_j^{0*} - mc_j) q_j^{0*} \Big], \tag{31}$$

where p_j^{0*} and p_j^{w*} are the equilibrium prices for model j under the baseline and w^{th} counterfactual scenario, respectively. q_j^{0*} and q_j^{w*} are the equilibrium number of sales for model j under the data and w^{th} counterfactual scenario, respectively.

Government Expenditure. The government expenditure per EV equals to the amount of EV subsidy per consumer in the sample data period. For the green license policy, the government expenditure is computed to be 0 as the cost of distributing green license plates is minimal.

Externalities. EV promotion policies have two effects on externalities (Holland et al. 2016; Guo and Xiao, 2022). The first is the substitution effect which refers to the shift from conventional vehicles (GVs) to EVs due to the promotion policies, leading to the reduction of vehicle emissions or pollution externalities. The second comes from the demand creation effect, which refers to the increased dynamics impacts due to higher EV demand. For instance, EV promotion policies may generate a network effect, whereby the purchase of EVs contributes to the development of EV infrastructure, enhancing the utility of EVs in the future. Besides, EV policies targeting the demand side of EV market might initiate a learning-by-doing effect, where the sale of EVs induces learning, leading to reduced cost for EVs. In our welfare analysis, we focus on the potential positive externalities, such as environmental gains due to the substitution effect in the former case. We do not account for the dynamic impacts in the latter case as our focus is on the static welfare.

To calculate the externalities led by the usage of EVs and GVs, I first estimate the annual external costs associated with the ownership and usage of electric vehicles (EVs) and gasoline vehicles (GVs). For estimation, I account for five external costs to analyze the welfare gains due to EV promotion policies. They include emissions of greenhouse and other gases (affecting global warming and air quality), crash costs (for partner vehicles in multi-vehicle crashes), roadway congestion, and space consumption. Summarizing the five sources of external cost, the marginal annual external cost (MEC_{EV}) per electric vehicle per mile traveled (VMT) is estimated to be in the range of \$0.033 - \$0.050 per VMT (Mitropoulos, Prevedouros and Kopelias, 2017). The marginal vehicle's external cost (MEC_{GV}) per gasoline vehicle mile traveled (VMT) is estimated to be in the range of \$0.140 - \$0.329 per VMT (Parry, Walls and Harrington, 2007; Lemp and Kockelman, 2008). According to the report *China Energy Conservation and New Energy Vehicle Development Annual Report (2017)*, the average miles traveled per vehicle per year (VMT) in Beijing in 2013 is around 10876 miles (17500 km). We take the estimate as the average VMT for both EVs and GVs in Beijing, 2015. By multiplying the factors above, we calculate the annual external cost due to the usage of the vehicle in group $g(g \in \{EV, GV\})$ as

$$AEC_g = MEC_g * VMT * Q_g. \tag{32}$$

To quantify the total externalities associated with the usage of EVs and GVs, we need to make assumption about the time horizon over which the external costs accrue. Though the license plate could last multiple vehicle usage, we assume the time horizon over which external cost accrues to be the vehicle lifetime to make sure our analysis would provide a lower bound on the welfare consequences. In China, the maximum legal age of vehicle usage is 15 years. However, the actual vehicle lifetime (LS) is much smaller than the legal age. Based on the statistics from China Association of Automobile Manufacturers, the average age of passenger cars in China is 8.17 years in 2015. According to the report *Real-world performance of battery electric passenger cars in China: Energy consumption, range, and charging patterns*, the average age of usage for an EV in 2014 is around 6-8 years. Given the assumption on time horizon of vehicle usage, the total external cost (TEC) due to vehicle usage is

$$TEC = \sum_{g \in \{EV, GV\}} AEC_g * LS_g. \tag{33}$$

Net Policy Cost. Given the assumption of minimum vehicle lifetime (6 years), I compute the lower bound of average net policy cost by summing up the average consumer surplus, producer profits, government expenditure and externalities.

Table 4: Welfare Comparison

Δ in \$ thousand	consumer surplus	producer profits	government spends	externalities	net gains
Subsidy	2.463	4.155	-7.223	[0.860, 2.830]	[0.245, 2.215]
Green license policy	0.606	5.839	0	[0.036, 0.118]	[6.481, 6.563]

***Notes**: The table displays the welfare consequences of subsidy and the green license policy, measured in a thousand of dollars per household in the sample data period (Beijing, 2015). The externalities of subsidy and the green license policy is calculated based on the assumption of minimum average vehicle lifetime (6 years) and provides the lower bound of externalities due to the usage of EVs and GVs.*

Table 4 presents the welfare outcomes of the subsidy and green license policy, measured in thousands of dollars per household. By aggregating consumer surplus, producer surplus, and government expenditures, we find that subsidies result in a total surplus decrease of approximately \$605 per household. In contrast, the green license policy proves to be more cost-effective, increasing the total surplus by roughly \$6,445 per household with minimal implementation cost. Considering the minimum externalities, the EV subsidy increases total welfare gains by at least \$860 to \$2,830 per household, while the green license policy increases total welfare gains at least by \$6,481 to \$6,563 per household. This indicates the overall efficiency of both policies. Besides, the welfare results indicate that under the green license policy, 90.59% of the welfare gains goes to the EV producers, whereas the subsidy results in a more balanced distribution of welfare gains between consumers and producers. This aligns with our previous findings that the green license policy enhances the market power of EV producers through market separation. In other words, the green license policy would re-allocate the profits between EV and GV producers, and thus encourage the development of EV technologies.

So far, we've quantified the impacts of both EV subsidy and the green license policy in deploying EVs and demonstrated the total welfare gains led by both policies. The results suggest that subsidy and the green license policy is beneficiary to the society given license quotas on GVs implemented. Nonetheless, for economies having not adopted the license quota policy, our analysis is not enough to provide policy implications as the license quota policy interacting with EV policies is unclear. For instance, license quota policy could lead to substantial deadweight loss due to the constraints on vehicle transactions and environmental gains because of less usage of vehicles.

6.3 License Quotas with the Green License Policy

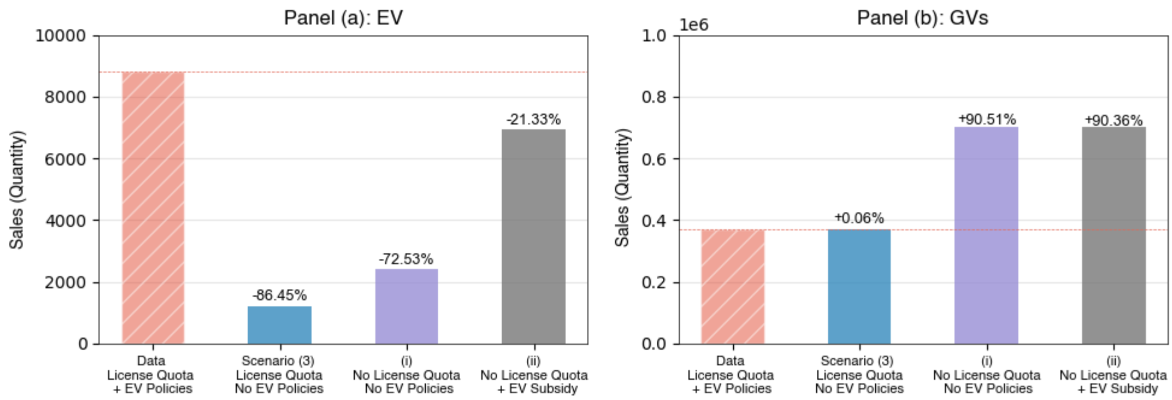
To further understand the feasibility of the license quota policy together with the EV promotion policies (subsidy and the green license policy), I evaluate the total welfare impacts of the license quotas policies interacting with the EV promotion policies in the context of Beijing, 2015.

In our analysis, I simulate two counterfactual scenarios: i) the null case where all the policies (the license quota policy, the green license policy and the EV subsidies) were removed; ii) the null case with EV subsidies where I remove the license quota policy and the green license policy but keep the EV subsidies in the context of Beijing, 2015.

6.3.1 Sales Impacts

Table 7 presents the simulation results. Total annual GV sales in Beijing would have increased by 90.51% if the license quota policy had been removed, indicating that the policy was effective in curbing vehicle consumption. Additionally, we find that annual EV sales would have decreased by 72.53% in the absence of both the license quota policy and EV promotion policies. Furthermore, without the license quota policy but with the implementation of EV subsidies, annual EV sales would have decreased by 21.33

Figure 7: Counterfactual Sales



__Notes__: The figure illustrates the counterfactual sales of EVs and GVs across three simulation scenarios for Beijing in 2015. In Scenario (3), we retain the license quota policy but eliminate both EV policies (subsidies and the green license policy). In Scenario (i), we remove the license quota policy along with both EV policies. In Scenario (ii), we remove the license quota policy and the green license policy but maintain the EV subsidies. The percentage changes indicate the variation in total sales, comparing the baseline sales (observed data) to each respective counterfactual scenario.

6.3.2 Welfare Analysis

I then evaluate the welfare consequences of implementing license quota policy interacting with the EV promotion policies (EV subsidy and the green license policy) based on consumers surplus, producer surplus, government expenditures and externalities associated with vehicle usage. This policy analysis offers insights on the adoption of license quota together with EV subsidy and the green license policy in the automobile market.

Consumer Surplus. I calculate the total compensation variations (CVs) to quantify the total consumer surplus changes due to the policies. The compensation variation calculation method is similar as illustrated above in equation (29). Different from previous analysis, I establish the baseline scenario as the null case with neither license quota policy nor EV-related policies implemented. Then I calculate the compensation variations from the null case to the counterfactual scenarios w^{th} where we (I) only implement license quota policy; (II) implement license quota policy and the green license policy; (III) implement license quota policy and EV subsidies; (IV) implement license quota policy and both EV policies. Then, we approximate the total changes in consumer surplus by

$$\Delta CS = -M \times \overline{CV^{w}}, \tag{34}$$

where M is the market size.

Producer Surplus. I compute the total profits changes from the null case to the counterfactual scenarios to measure the producer surplus changes resulting from the policies. The total changes in producer surplus are written as

$$\Delta PS = \sum_j \Big[(p_j^{w*} - mc_j)q_j^{w*} - (p_j^{0*} - mc_j)q_j^{0*}\Big], \tag{35}$$

where p_j^{0*} and p_j^{w*} are the equilibrium prices for model j under the baseline and w^{th} counterfactual scenario ($w = I, II, III, IV$), respectively. mc_j is the marginal cost of the product j. q_j^{0*} and q_j^{w*} are the equilibrium number of sales for model j under the data and w^{th} counterfactual scenario, respectively.

Externalities. I account for the externalities due to the usage of EVs and GVs in the welfare analysis. As mentioned above, we summarize five external cost associated with vehicle usage including emissions of greenhouse and other gases (affecting global warming and air quality), crash costs (for partner vehicles in multi-vehicle crashes), roadway congestion, and space consumption. I use the same estimates for the marginal average external costs (MEC) per vehicle per mile, VMT and minimum vehicle lifetime as described above. Based on the assumption of minimum vehicle lifetime (6 years), we estimate the lower bound of total external environmental gains due to less vehicle usage led by license quota policy to be around \$3.05 - \$7.16 billion.

Table 5 displays the total welfare changes due to the implementation of license quota policy along with EV subsidies and the green license policy. From the environment perspective, license quota policy efficiently decrease the total number of GVs on the road and thus lead to substantial environmental welfare gains around \$3.05 - \$7.16 billions. Overall, the net effect of the license quota system on social welfare depends on the assumption of the vehicle's lifetime. Given the minimum assumption of vehicle lifetime (6 years), the lower bound of total welfare impacts of license quota policy are approximate to be -0.55

billion dollars indicating possibly low efficiency of the quota and allocation system. However, if the vehicle lifetime is expected to be longer than 7.07 years, the license quota policy will lead to positive total welfare gains which provide important policy implications for the economies that face similar environmental problems (congestion, pollution) as Beijing.

Conditional on the implementation of a license quota policy, we find that adoption of both subsidies and the green license policy under the license quota policy provides higher social welfare indicating it is more efficient to adopt the green license policy and EV subsidies under license quota policy.

Moreover, our analysis of license quota policy is based on a lottery system. An auction system which could increase the government revenue would have made the license quota policy substantially more efficient. The clearing price of a license plates in our analysis is estimated to be around \$13,859 in Beijing, 2015. As a point of reference, the average bid price for a license plate is around \$13,575 in Shanghai in 2015. Holding all the others unchanged, adopting an auction system to allocate the license plates in Beijing implies additional \$1.47 billion government revenue from around 105,600 license quotas implying even larger welfare gains of adopting the license quota policy with an auction system.

Our evaluations show simply applying the license quota policy did lead to huge environmental gains in less GV usage but large deadweight loss. However, the net welfare impacts of license quota policy under the lottery system depends on the assumption of vehicle lifetime and the estimates for external cost. It also supports the efficiency of green license plate and EV subsidies in promoting the diffusion of electric vehicles.

6.4 Whitelist with the Green License Policy

Beyond EV subsidies and the green license policy, Beijing's approach to promoting electric vehicles includes a less conspicuous, protective practice known as the whitelist policy. Detailed in Section 2, this policy permits only the EVs specified on an approved list to benefit from the city's promotional efforts. Barwick et al. (2024) have argued that the whitelist policy on EV batteries has significantly increased the market share of Chinese battery manufacturers, nearly doubling it. Nonetheless, the whitelist has been subject to widespread

Table 5: Welfare Results

Baseline	(I)	(II)	(III)	(IV)
License Quota Policy (lottery)	YES	YES	YES	YES
EV Subsidy		YES		YES
Green License Policy			YES	YES
Regular license quotas	105,600	105,600	105,600	105,600
EVs deployed	2,418	3,658	3,367	8804
Δ in $ billion				
Consumer surplus	-1.85	-1.84	-1.84	-1.81
Producer surplus	-1.74	-1.73	-1.72	-1.68
Government subsidy	0	-0.024	0	-0.064
Total surplus	-3.59	-3.57	-3.56	-3.55
Annual external gains	[0.51,1.19]	[0.51,1.19]	[0.51,1.19]	[0.51,1.19]
Total external gains (6 years)	[3.05, 7.16]	[3.05, 7.16]	[3.04,7.15]	[3.03, 7.14]
Net cost (gains)	[-0.55, 3.57]	[-0.53,3.59]	[-0.52,3.59]	[-0.52,3.59]
Minimum average vehicle lifetime (years)	7.07	7.00	6.98	6.96

***Notes**: The table shows the total welfare differences between the baseline case (where neither the license quota policy, EV subsidy, nor the green license policy is implemented) and the counterfactual scenarios during the sample data period (Beijing, 2015). Welfare changes are measured in billions of dollars per year. The total externalities represent the lower bound of environmental gains due to reduced vehicle usage, based on an assumed minimum vehicle lifetime of 6 years. The minimum average vehicle lifetime indicates the estimated duration required to achieve zero net gains under the corresponding policy.*

critique, being labeled as a form of local protectionism.[1] (Barwick, Cao and Li, 2021).

In this research, our structural model enables the examination of the equilibrium effects of discontinuing the EV whitelist via counterfactual simulations. This study leverages the policy experiment in Beijing, where the whitelist policy is notably more stringent than in other major cities. Specifically, only battery electric vehicles that meet certain range criteria are eligible for subsidies and the green license policy in Beijing.[2]

To assess the consequences of the whitelist policy, I conduct simulations to predict the equilibrium market shares and prices under a counterfactual scenario where the EV whitelist is abolished in Beijing. This allows all available EV models in the market, including both battery electric and plug-in hybrid electric vehicles, to benefit from the green license policy. In our simulation scenario in the context of Beijing (2014 -2015), fourteen new trim-level EV models were added, including the Toyota Prius, Toyota Camry, BYD Qin, and Nissan Murano, among others. Given that subsidy amounts are typically associated with specific model types, we exclude subsidies in this counterfactual analysis. In this case, we assume the previously discussed counterfactual scenario (1) where we remove the subsidy but keep the whitelist as the baseline scenario. To isolate the effects of eliminating the whitelist policy, I compare our simulation results with those in the baseline scenario and discuss the impacts of eliminating the whitelist policy across three dimensions: sales, pricing, and the substitution patterns within the group of EVs previously on the list versus those that were not.

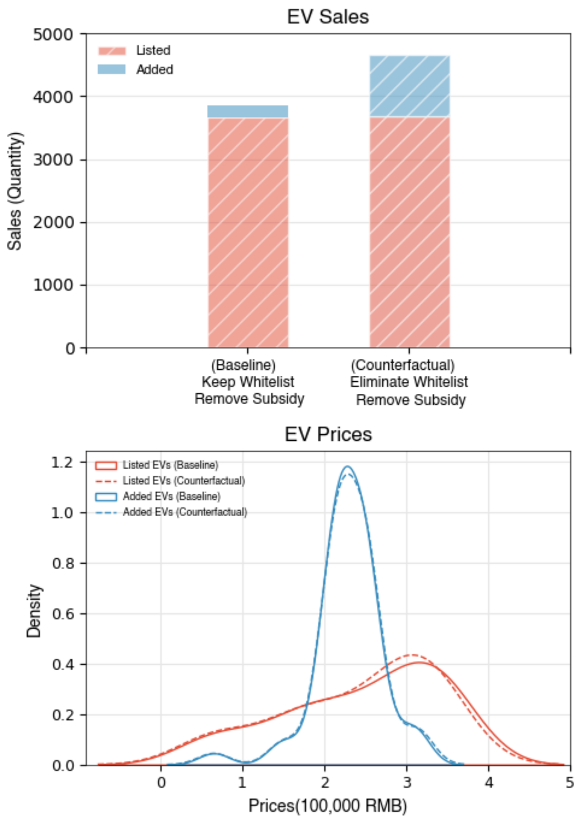
Figure 8 presents the equilibrium sales and prices of EVs in the baseline and counterfactual scenario. The equilibrium impacts on GVs are not displayed as the impacts are minimal. The results suggest that 1) eliminating the whitelist could lead to a significant increase in the sales of EVs originally off the list but almost has no effect on the sales of EVs on the list; 2) equilibrium prices of EVs originally not on the list have increased slightly had the whitelist been eliminated. Our counterfactual analysis implies that eliminating the whitelist would be a beneficiary practice to promote the diffusion of EV; 3) eliminating the whitelist in the green license policy does not affect the equilibrium sales and prices of

[1] Referenced from a report by the China Association of Automobile Manufacturers

[2] Conversely, in other major cities such as Shanghai, plug-in hybrid electric vehicles qualify for a reduced amount of subsidy but are still eligible for the green license policy.

gasoline vehicles. We do not observe large substitution between EVs on the list and off the list as consumers show large heterogeneity towards battery electric vehicles. The welfare analysis shows that total consumer surplus will increase by 0.188 million dollars and total producer profits will increase by 4.548 million dollars if we simply eliminate the whitelist in the green license policy.

Figure 8: Counterfactual Results



Notes: *The figure plots the equilibrium sales and prices in the baseline scenario and in the counterfactual scenario where I eliminate the whitelist in the context of Beijing, 2015. The electric vehicle (EV) models are classified as listed EVs which were on the whitelist and added EVs which are included in the counterfactual where we eliminate the whitelists. The upper panel represents the total sales of listed EVs and added EVs in the baseline and counterfactual scenario. The lower panel displays the price distribution of listed EVs and added EV in the baseline and counterfactual scenario*

7 Conclusion

Over the last decade, a variety of support policies for electric vehicles (EVs) have been instituted in key markets, stimulating a major expansion of electric car markets. My study quantifies the impacts of two EV support policies—EV subsidies and the green license plate policy—in the world's largest EV market, China. It provides an empirical analysis on EV-related policies and sheds light on how and to what extent the government can promote the demand for electric vehicles and address environmental concerns associated with conventional vehicles through demand-side EV policies.

Employing a two-stage discrete choice model for vehicle demand, I find that the impact of the green license plate policy, with its very low implementation cost, on promoting EV sales in Beijing is comparable to a subsidy of $7,223 per EV in 2015. Additionally, a combination of the two EV support policies is more effective than the subsidy alone. Moreover, our counterfactual analysis shows that there is little substitution from gas cars to EVs under both promotion policies during the sample data period in Beijing, implying limited environmental gains, contrary to policy-makers' expectations. My analysis also demonstrates that adopting the green license plate policy in a single-producer scenario could lead to high market power for the EV producer, due to the policy segmenting the vehicle market. This finding offers guidance on designing future EV policies, highlighting the importance of accounting for market structure in policy analysis of the EV market and industry.

Although my results may present a compelling case for the green license plate policy, several important assumptions in my model warrant caution. First, my model assumes no product-level or firm-level entries during the sample period. Second, it assumes no technology adoption or dynamics on the demand and supply sides. Third, my model and analysis are based on the vehicle quota system, whose stringency of implementation significantly affects the effectiveness of the green license plate policy. Since the vehicle quota system is often associated with large deadweight losses and potential environmental gains, policy-makers should carefully evaluate vehicle market conditions before adopting a quota or a green license plate policy.

Most importantly, for policymakers concerned with the performance of EV support policies, there are several aspects of this current analysis that can be extended. First, my demand estimation and policy analysis are based on vehicle data from 2010-2015, an early stage of China's EV market development. Our demand estimation shows low substitutability between gasoline vehicles (GVs) and EVs, implying low external environmental gains from EV policies during the sample period. However, this may not be the case now. There has been a major expansion of powerful and popular EV models in China and other countries, suggesting that the environmental gains from EV-related policies may no longer be negligible. Second, my research does not address the network effects of technology adoption on both the demand and supply sides. Beyond environmental concerns, policymakers may have additional reasons to support EV demand, such as technology improvement and industry development. Third, there are other EV-related support policies not accounted for in this research. For example, government investment in charging infrastructure or battery technologies could be valuable.

References

Abaluck, Jason and Abi Adams-Prassl (2021) "What Do Consumers Consider Before They Choose? Identification from Asymmetric Demand Responses," *The Quarterly Journal of Economics*, 136 (3), 1611–1663, 10.1093/qje/qjab008.

Agarwal, Nikhil and Paulo Somaini (2022) "Demand Analysis under Latent Choice Constraints," *Working Paper*, 10.3386/w29993.

Albuquerque, Paulo and Bart J. Bronnenberg (2012) "Measuring the Impact of Negative Demand Shocks on Car Dealer Networks," *Marketing Science*, 31 (1), 4–23.

Barwick, Panle Jia, Shengmao Cao, and Shanjun Li (2021) "Local Protectionism, Market Structure, and Social Welfare: China's Automobile Market," *American Economic Journal: Economic Policy*, 13 (4), 112–151, 10.1257/pol.20180513.

Barwick, Panle Jia, Hyuksoo Kwon, Shanjun Li, and Nahim Zahur (2024) "Drive Down the Cost: Learning by Doing and Government Policy in the Global Electric Vehicle Battery Industry," *Working Paper*.

Berry, Steven (1994) "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, 25 (2), 242–262, 10.2307/2555829.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995) "Automobile Prices in Market Equilibrium," *Econometrica*, 63 (4), 841–890, 10.2307/2171802.

——— (2004) "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market," *Journal of Political Economy*, 112 (1), 68–105, 10.1086/379939.

Brenkers, Randy and Frank Verboven (2006) "Liberalizing a Distribution System: The European Car Market," *Journal of the European Economic Association*, 4 (1), 216–251.

Bresnahan, Timothy F. (1987) "Competition and Collusion in the American Automobile Industry: The 1955 Price War," *The Journal of Industrial Economics*, 35 (4), 457–482, 10.2307/2098583.

Chen, Chia-Wen, Wei-Min Hu, and Christopher R. Knittel (2021) "Subsidizing Fuel-Efficient Cars: Evidence from China's Automobile Industry," *American Economic Journal: Economic Policy*, 13 (4), 152–184, 10.1257/pol.20170098.

Gowrisankaran, Gautam and Marc Rysman (2012) "Dynamics of Consumer Demand for New Durable Goods," *Journal of Political Economy*, 120 (6), 1173–1219, 10.1086/669540.

Grieco, Paul L E, Charles Murry, and Ali Yurukoglu (2023) "The Evolution of Market Power in the U.S. Automobile Industry*," *The Quarterly Journal of Economics*, qjad047, 10.1093/qje/qjad047.

Grigolon, Laura and Frank Verboven (2014) "Nested Logit or Random Coefficients Logit? A Comparison of Alternative Discrete Choice Models of Product Differentiation," *The Review of Economics and Statistics*, 96 (5), 916–935.

Guo, Xiaodan and Junji Xiao (2022) "Welfare Analysis of the Subsidies in the Chinese Electric Vehicle Industry," *Journal of Industrial Economics*.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates (2016) "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors," *American Economic Review*, 106 (12), 3700–3729, 10.1257/aer.20150897.

Holland, Stephen P., Erin T. Mansur, and Andrew J. Yates (2021) "The Electric Vehicle Transition and the Economics of Banning Gasoline Vehicles," *American Economic Journal: Economic Policy*, 13 (3), 316–344, 10.1257/pol.20200120.

Kelly, Brian (2014) "The Pass-Through of Subsidies to Price," *Journal of World Trade*, 48 (2).

Lemp, Jason D. and Kara M. Kockelman (2008) "Quantifying the External Costs of Vehicle Use: Evidence from America's Top-Selling Light-Duty Models," *Transportation Research Part D: Transport and Environment*, 13 (8), 491–504, 10.1016/j.trd.2008.09.005.

Li, Shanjun (2018) "Better Lucky Than Rich? Welfare Analysis of Automobile Licence Allocations in Beijing and Shanghai," *The Review of Economic Studies*, 85 (4), 2389–2428, 10.1093/restud/rdx067.

Li, Shanjun, Xianglei Zhu, Yiding Ma, Fan Zhang, and Hui Zhou (2020) "The Role of Government in the Market for Electric Vehicles: Evidence from China," https://elibrary-worldbank-org.ezaccess.libraries.psu.edu/doi/epdf/10.1596/1813-9450-9359, 10.1596/1813-9450-9359.

Mitropoulos, Lambros K., Panos D. Prevedouros, and Pantelis Kopelias (2017) "Total Cost of Ownership and Externalities of Conventional, Hybrid and Electric Vehicle," *Transportation Research Procedia*, 24, 267–274, 10.1016/j.trpro.2017.05.117.

Nevo, Aviv (2000) "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand," *Journal of Economics & Management Strategy*, 9 (4), 513–548, 10.1111/j.1430-9134.2000.00513.x.

Parry, Ian W. H., Margaret Walls, and Winston Harrington (2007) "Automobile Externalities and Policies," *Journal of Economic Literature*, 45 (2), 373–399, 10.1257/jel.45.2.373.

Petrin, Amil (2002) "Quantifying the Benefits of New Products: The Case of the Minivan," *Journal of Political Economy*, 110 (4), 705–729, 10.1086/340779.

Pless, Jacquelyn and Arthur A. Van Benthem (2019) "Pass-Through as a Test for Market Power: An Application to Solar Subsidies," *American Economic Journal: Applied Economics*, 11 (4), 367–401, 10.1257/app.20170611.

Qin, Ping, Yifei Quan, Antung A Liu, Joshua Linn, and Jun Yang (2021) "The Welfare Cost of Beijing's Lottery Policy—Evidence from a Contingent Valuation Survey," *Working Paper*, 29.

Springel, Katalin (2021) "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives," *American Economic Journal: Economic Policy*, 10.1257/pol.20190131.

Xiao, Junji, Xiaolan Zhou, and Wei-Min Hu (2017) "WELFARE ANALYSIS OF THE VEHICLE QUOTA SYSTEM IN CHINA: WELFARE ANALYSIS OF VQS IN CHINA," *International Economic Review*, 58 (2), 617–650, 10.1111/iere.12229.

Xing, Jianwei, Benjamin Leard, and Shanjun Li (2021) "What Does an Electric Vehicle Replace?" *Journal of Environmental Economics and Management*, 107, 102432, 10.1016/j.jeem.2021.102432.

Zheng, Yunhan, Joanna Moody, Shenhao Wang, and Jinhua Zhao (2021) "Measuring Policy Leakage of Beijing's Car Ownership Restriction," *Transportation Research Part A: Policy and Practice*, 148, 223–236, 10.1016/j.tra.2021.03.008.

Appendices

A Policy Summary

Policy Summary

Year	Month	End	City	License Allocation	NEV License	Central Subsidy	Local Subsidy
2010	1		Shanghai	auction			
2010	6	2012-12	Shanghai			YES	
2011	5	2012-12	Shanghai				YES
2013	4		Shanghai	mixed			
2013	9	2015-12	28 cities			YES	
2014	4	2015-12	Shanghai		free license		
2011	1		Beijing	lottery			
2013	9	2015-12	28 cities			YES	
2014	1	2017-12	Beijing				YES
2014	2		Beijing		NEVs lottery		
2014	12		Beijing				YES
2015	11		Beijing		free licenses		
2012	8		Guangzhou	mixed	NEVs lottery		
2012	12	2014-3	Guangzhou				YES
2013	9	2015-12	28 cities			YES	
2014	11	2015-12	Guangzhou				YES
2013	9	2015-12	28 cities			YES	
2014	2		Tianjin	mixed	NEVs lottery		
2014	7	2015-12	Tianjin				YES
2013	9	2015-12	28 cities			YES	
2014	5		Hangzhou	mixed	free license		
2014	10	2015-12	Hangzhou				YES
2013	9	2015-12	28 cities			YES	
2015	2		Shenzhen	mixed	NEVs lottery		
2015	8		Shenzhen				YES

Notes: *I list the time when the city announced license quota policy and green license policies, and also the time when the government started to distribute central or local subsidies. There are some other policy benefits for EV users not listed above but controlled by the city fixed effects. For instance, EV users can enjoy unlimited parking rights in Beijing and Shanghai.*

B License Quota Policy and Allocation Systems

B.1 Beijing

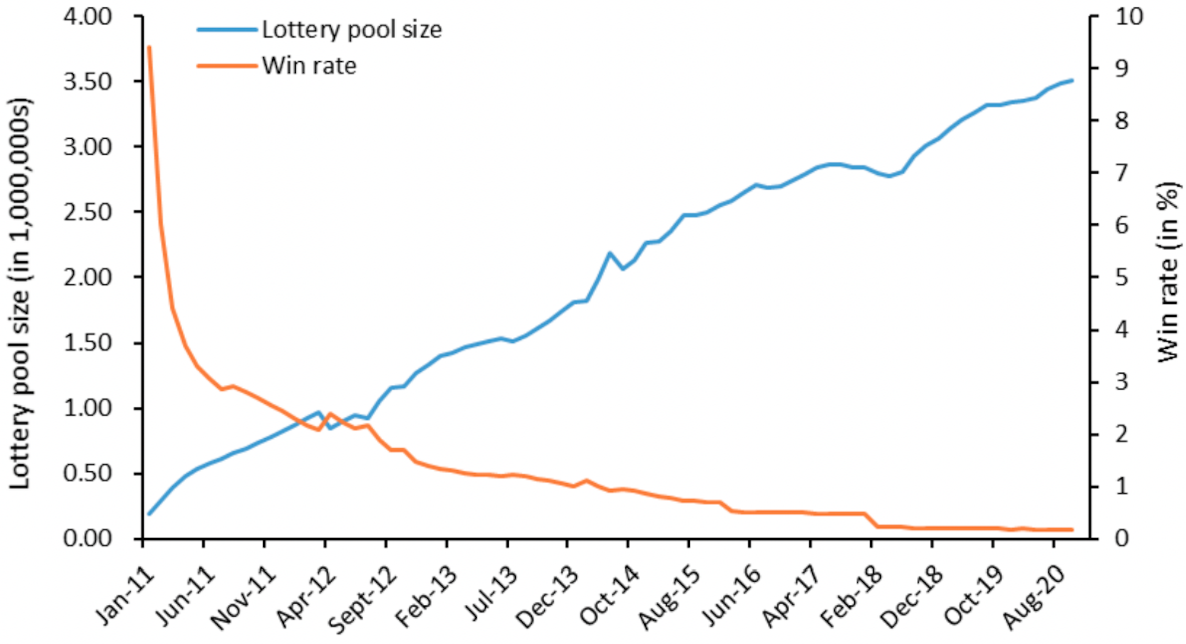
As the car ownership keep increasing from 2006, traffic congestion and air pollution become more and more severe in large cities. To address these two issues, municipal governments started to enact the policy of capping new licenses plates for conventional cars and issuing green license plates for electric vehicles.

License Quota. Referring to Li (2018), "on December 23, 2010, the Beijing municipal government introduced a license quota system to control the number of new vehicle registrations. Starting from January 2011, a lottery system has been in place, distributing approximately 20,000 licenses monthly between 2011 and 2013, with the yearly quota reduced to 150,000 post-2013. This policy applies to first-time vehicle buyers, individuals acquiring a used vehicle, receiving a vehicle as a gift, or transferring a vehicle registration from outside Beijing. Owners replacing a scrapped vehicle can reassign their existing license to a new vehicle, bypassing the need for a new license. Eligibility for participation extends to both residents of Beijing and non-residents who have contributed to the city's income tax for a minimum of five years."

License Allocation. The licenses under the quota system in Beijing are assigned to winners through random drawings. The winners can then use the license to register their vehicles. The winners are determined in the license lottery pools allocated monthly. The first lottery was held on 26th, January 2011 and 17,600 private licenses were allocated among 187,420 participants. The winning odds reduced to 1:100 by the end of 2013 and further to 1/725 in August 2016, due to the accumulation of pent-up demand over time as well as future buyers entering into the lottery pool. Figure 9 shows monthly winning odds and the number of participants. After winning the lottery, the winners have six months to register a new vehicle before the winning certificates become expired. Once expired, the license quota recycles back for distribution in future lotteries. The winners who allow their licenses to expire will not be permitted to participate in the lottery within the next three years.

License Transfer. According to China's Motor Vehicle Registration Regulations pub-

Figure 9: The Size of the Beijing Lottery Pool and Lottery Win Rates (2011–2020)



Note: the figure is cited from Qin, Quan, Liu, Linn and Yang (2021).

lished in 2008, used license plate are not allowed to be transferred. If the buyer does not have his or her own license plate, then even if he or she buys the used car, it is useless because there is no license plate on it. It prohibited buyers in these cities from reselling the license plate. Although there is anecdotal evidence that some transferring(reselling/renting) occurred by having vehicle registered under the winner but paid and used by another person, this is not known to be widespread because the legal owner (the winner) not only has the liabilities in paying annual registration fee, traffic fines and emission inspections, but also is liable for damages and injuries in accidents.

Registering in the Neighborhood. Barriers are in place to prevent the residents from registering vehicles in neighboring provinces. In Beijing, a temporary driving permit is needed to be able to drive an out-of-state vehicle in Beijing. More importantly, the vehicles with an out-of-state license plate are banned from entering the central part of these cities (within which the vast majority of business and population are located) during rush hours. So this avoidance behavior is also not likely to be widespread.

B.2 Shanghai

License Allocation. Among all the cities with quota constraints, Shanghai is the first city to implement a vehicle license quota system, and it auctioned its first license in 1986. Initially, it was a sealed-bid auction where reservation prices and quota levels varied across vehicles produced in Shanghai, non-Shanghai produced vehicles, and imports. In 2003, a unified auction system without a reservation price was put in place for domestic vehicles and imports. The online auction format during 2008 to 2012 can be characterized as a multi-unit, discriminatory (pay as you bid), and dynamic auction.

According to Li(2018), the average bid price increased from 23,370 to 69,346 Yuan during this period. The winners are required to purchase a new vehicle within three months before the license expires. The vehicle and the license cannot be transferred within the first year of registration. Similar to Beijing, vehicles registered outside of Shanghai are not allowed to use the major roads during rush hours. "Although there is anecdotal evidence that some households choose to register their vehicles in neighboring provinces due to high license prices, this phenomenon is not believed to be widespread." As I'm focusing on the implicit value of winning lottery, I will exclude Shanghai from my analysis.

B.3 Other Cities

License Allocation. Besides the lottery application system in Beijing and the auction allocation system in Shanghai, the others five cities with the license quota system (Hangzhou, Tianjin, Guangzhou, Shenzhen, and Guangzhou) adopted a mixed allocation system to allocate the license plates. In the cities with mixed allocation system, the total number of license plates is also strictly constrained by the government.

C Effect of License Quota Policy

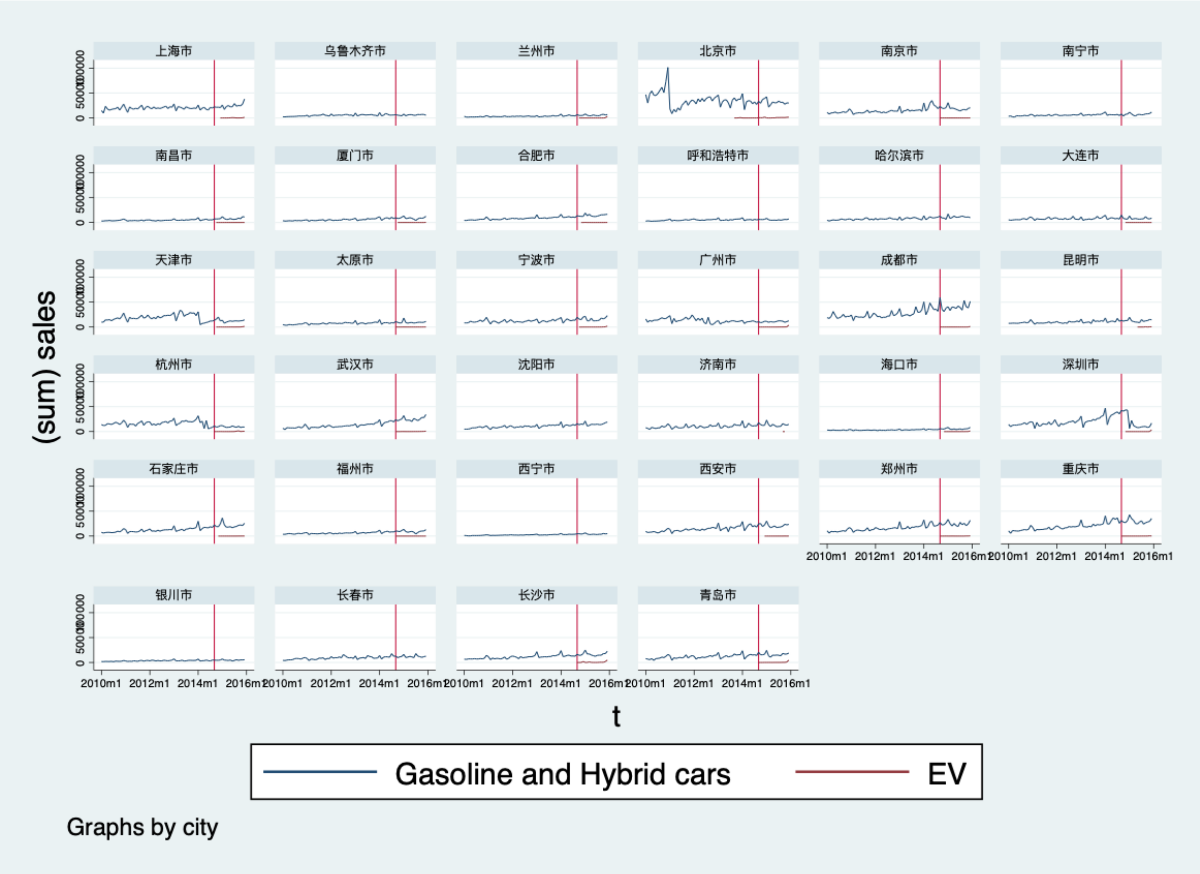
To understand how the quota policies affect the sales of conventional cars and EVs in Beijing, I first check quantify sales changes of gasoline cars before and after the policy implementation. As shown in Figure 10, total number of gasoline car sales decrease sharply following the policy implementation in Beijing and Tianjin offering an indication that the policy did restrict consumers' choices of buying cars. By comparing with Tianjin and Shanghai, we rule out the possibility that the sales decline is led by seasonality or time trend. The decline cannot simply be driven by prices because we did not observe sharp sales decline in Shanghai at the policy time. The dramatic decrease in vehicle sales since the implementation of the quota constraint policy reflects the stringency of the policy relative to the demand for new vehicles. The difference between vehicle sales and the number of licenses allocated comes from the consumers who scrap the used vehicle and buy a new car with the old license.

Figure 10: Total Number of Sales in Beijing

(Graph without seasonality will be added later)

Next, I examine the sales changes of EVs across cities over time to understand consumers' preference for EVs. Figure 11 shows 1) the sales of EVs remained to be zero in most major cities in China during 2010-2014 implying a lack of enthusiasm for EVs from consumers and automakers, at the beginning of its implementation; 2) buyers of EVs occurred immediately after the EV license policy implementation in Beijing in January 2014 indicating consumer's choices shifted by the quota constraints; 3) the sales of EVs in cities other than Beijing increased after the August 2014 possibly due to subsidy programs or increasing available vehicle models or better-equipped EV-related facilities. To rule out the possibility that the difference are driven by vehicle characteristics, I compare the characteristics of EV models on and off the list and find the sales changes of EVs are not led by changes of characteristics but though the policy changes.

Figure 11: EV Sales - Beijing



D Outside Option

The market share of outside option is composed of six parts. It includes the market share of re-purchasers i_2 who chooses the outside option in stage 2, the market share of first-time buyers i_1 who choose outside option in stage 1, the market share of first-time buyers i_1 who apply for the regular license plate but lose the lottery in stage 1, the market share of first-time buyers i_1 who apply for the EV license but lose the lottery in stage 1, the market share of first-time buyers i_1 who win the regular license in stage 1 but choose not to purchase in stage 2, the market share of first-time buyers i_1 who win the EV license in stage 1 but choose not to purchase in stage 2.

$$
\begin{aligned}
s_{0mt|\textbf{post}} &= \int Pr_{i_k 0mt}(\delta,\mu)dF(\mu_{i_k mt}, i_k, \rho_{mt}, l_{i_k mt})dF(\mu_{i_k 0mt}, i_k, \rho_{lmt}, l_{i_k mt}) \\
= \quad & \int \underbrace{Pr_{i_2 0mt}(\delta,\mu|i_2)\times Pr(i_k = i_2)}_{\text{outside choice probability of re-purchasers } i_2} \; dF(\mu_{i_2 jmt}) \\
+ \quad & \int \Big[\qquad \underbrace{Pr(l_{i_1 mt} = 0) * Pr(i_k = i_1)}_{\text{outside choice probability of first-time buyers } i_1 \text{ in Stage 1}} \\
+ \quad & \underbrace{(1-\rho_{l_r mt})\times Pr(l_{i_1 mt} = l_r)\times Pr(i_k = i_1)}_{\text{probability of first-time buyers } i_1 \text{ losing the lottery in Stage 1}} \\
+ \quad & \underbrace{(1-\rho_{l_e mt})\times Pr(l_{i_1 mt} = l_e)\times Pr(i_k = i_1)}_{\text{probability of first-time buyers } i_1 \text{ losing the lottery in Stage 1 (0)}} \\
+ \quad & \underbrace{Pr_{i_1 0mt}(\delta,\mu|i_1, \text{win the regular license})\times \rho_{l_r mt}\times Pr(l_{i_1 mt} = l_r)\times Pr(i_k = i_1)}_{\text{outside choice probability of first-time buyers } i_1 \text{ who wins a regular license}} \\
+ \quad & \underbrace{Pr_{i_1 0mt}(\delta,\mu|i_1, \text{win the EV license})\times \rho_{l_e mt}\times Pr(l_{i_1 mt} = l_e)\times Pr(i_k = i_1)}_{\text{outside choice probability of first-time buyers } i_1 \text{ who wins a EV license}} \Big] dF(\mu_{i_1 jmt}).
\end{aligned} \tag{36}
$$

E Moment Summary

format:

2010Q1 Beijing share of regular license: 0.042523481 ; share of EV license: NA ... 2014Q1 Beijing share of regular license: 0.259834749 ; share of EV license: 0.000238075

F Model-to-Model Own- and Cross- Price Elasticities

Table 6: Sample of Model-to-Model Price Elasticities

Brand Make	**Price (RMB)**	BYD F0	Gelly Jyoting SC7	Volkswagen Santana	Ford Focus	Honda Civic	Hyundai Tussan	Mazda Speed6	Chevrolet Captiva	Toyota Prius	Audi A4L	Infiniti Q50	Mercedes-Benz E320L	Chery eQ	Zotye ZDD2	JAC HeyueiEV	Toyota Camry	BYD Tang	BAIC EV200
BYD F0	50,456	-1.5586	0.0001	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001	0.0001	0.0001	0.0011	0.0007	0.0001	0.0013
Gelly Jyoting SC7	36,197	0.0000	-1.1181	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001	0.0001	0.0001	0.0011	0.0007	0.0001	0.0013
Volkswagen Santana	112,133	0.0000	0.0001	-3.4637	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0002	0.0000	0.0001	0.0010	0.0007	0.0001	0.0015
Ford Focus	121,415	0.0000	0.0000	0.0001	-3.7505	0.0001	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0002	0.0000	0.0001	0.0010	0.0007	0.0001	0.0015
Honda Civic	131,436	0.0000	0.0000	0.0001	0.0000	-4.0600	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0003	0.0000	0.0001	0.0010	0.0007	0.0001	0.0016
Hyundai Tuscan	155,034	0.0000	0.0000	0.0001	0.0000	0.0001	-4.7890	0.0000	0.0001	0.0001	0.0000	0.0000	0.0003	0.0000	0.0001	0.0009	0.0007	0.0001	0.0017
Mazda Speed6	160,581	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	-4.9603	0.0001	0.0001	0.0000	0.0000	0.0003	0.0000	0.0001	0.0009	0.0007	0.0001	0.0017
Chevrolet Captiva	237,675	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	-7.3418	0.0001	0.0000	0.0000	0.0005	0.0000	0.0001	0.0009	0.0008	0.0001	0.0021
Toyota Prius	253,658	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001	-7.8354	0.0000	0.0000	0.0006	0.0000	0.0001	0.0008	0.0008	0.0001	0.0023
Audi A4L	256,479	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001	-7.9226	0.0000	0.0006	0.0000	0.0001	0.0008	0.0008	0.0001	0.0023
Infiniti Q50	366,479	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0001	0.0001	0.0001	-11.3205	0.0012	0.0000	0.0000	0.0007	0.0010	0.0002	0.0041
Mercedes-Benz E320L	587,607	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001	0.0002	0.0001	0.0001	-18.1476	0.0000	0.0001	0.0011	0.0029	0.0006	0.0189
Chery eQ	69,800	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.7051	0.0995	1.4443	1.0554	0.1325	2.0053
Zotye ZDD2	152,800	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0542	-3.2351	1.3965	1.1042	0.1446	2.3248
JAC HeyueiEV	169,800	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0527	0.0935	-2.4740	1.1120	0.1472	2.4064
Toyota Camry	259,800	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0433	0.0830	1.2482	-6.8867	0.1635	3.0257
BYD Tang	300,000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0379	0.0758	1.1527	1.1405	-9.0943	3.4497
BAIC EV200	346,900	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0308	0.0655	1.0121	1.1337	0.1852	-5.2511

Notes: *The table displays the sample of model-to-model price elasticities for selected vehicle products in a single market. The brands and make-level models in the green color are electric vehicles (EVs) qualified for the promotion policies in Beijing. The prices displayed are the unsubsidized prices. The numbers in the blue cells are the own price elasticities for the selected conventional vehicles.*

G Model Fitness

Table 7: Model fitness

	Time	Data	Model	Diff
Moment 1				
Evs as Second Choices for EV models	2015	0.6600	0.6597	-3.00E-04
Moment 2				
Outside Shares	2014-2015	0.0204	0.0203	-4.44E-05
Moment 3				
Regular License Application				
$Pr(l_{i_1} = l_r)$	2014Q1	0.2481	0.2481	2.26E-06
	2014Q2	0.2715	0.2715	9.09E-07
	2014Q3	0.2898	0.2897	-1.12E-05
	2014Q4	0.2916	0.2915	-7.85E-05
	2015Q1	0.3087	0.3087	4.47E-08
	2015Q2	0.3183	0.3182	-4.37E-05
	2015Q3	0.3346	0.3343	-3.12E-04
	2015Q4	0.3376	0.3376	-8.54E-06
EV License Application				
$Pr(l_{i_1} = l_e)$	2014Q1	0.0002	0.0002	6.21E-07
	2014Q2	0.0003	0.0003	8.03E-06
	2014Q3	0.0002	0.0003	4.60E-05
	2014Q4	0.0003	0.0005	2.71E-04
	2015Q1	0.0003	0.0003	6.07E-06
	2015Q2	0.0005	0.0006	1.40E-04
	2015Q3	0.0010	0.0020	9.26E-04
	2015Q4	0.0023	0.0023	2.80E-05

Notes: *Moment 1 relies on the national survey data among EV consumers in 2015. Moment 2 and Moment 3 is based on Beijing license application data and the quota usage information during 2014-2015. We take the average of outside shares data among regular license winners from the bi-monthly data in Beijing as Moment 2. We take the average outside shares data among regular license winners from the bi-monthly data in Beijing as Moment 2.*

H Empirical Methods

In this appendix, I explain our empirical method in performing the counterfactual analysis in Section 7 and present the technique details.

To start with, we make the following assumptions in the counterfactual analysis. First, our simulations hold the consumers' taste parameters, marginal costs of production, and product offerings fixed under different counterfactual scenarios. A possible concern about this assumption is that both subsidy and the green license policy attract more consumers to electric vehicles, thereby possibly motivating firms to introduce more EV models. If this is the case, our counterfactual analysis would underestimate the effects of both policies on the EV market. However, the empirical evidence suggests that the policies have not significantly changed the number of EV models available in the market.

H.1 Subsidy Pass-Through

Subsidies in Competitive Markets