Demand-side Policies in Electric Vehicles Adoption: Evidence from Beijing

Wen Tian *

[*Job Market Paper*] †

October 24, 2024

Abstract

In response to global climate change and environmental problems, policymakers worldwide have implemented various policies to increase the adoption of electric vehicles (EVs). This paper employs a structural model to evaluate the impacts of two demand-side interventions including EV subsidies and the green license plate policy on the adoption of EVs and examines the welfare impacts of these policies. Using data from China's vehicle industry, I estimate a demand model that endogenizes consumer license plate choices and vehicle purchase decisions while accounting for consumer demographic heterogeneity. On the supply side, I estimate marginal costs assuming Nash-Bertrand pricing. My counterfactual analysis shows that the green license plate policy was strikingly effective in promoting EV sales, equivalent to approximately $7,839 per EV in subsidies during the data period in Beijing, but it also led to increased market power for EV producers. I also find that the green license plate policy and EV subsidies could efficiently improve net welfare when considering environmental externalities.

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

†I am indebted to Paul Grieco, Mark Roberts, Conor Ryan, and Karl Schurter for their invaluable guidance and support throughout this project. I am deeply thankful for the comments, suggestions, and help from Linlin Fan, Marc Henry, and Beitong Zhang. I greatly appreciate Mandy Mantian Hu, and Matthew Ce Shi for allowing me to use the data in this project. All remaining errors are my own.

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.

In China, the local government in Beijing has introduced multiple demand-side incentives to promote the use of electric vehicles (EVs) 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 (referred to as GLP policy hereafter) provides EV buyers with distinctive license plates and grants them a registration privilege in Beijing, where vehicle purchases are subject a stringent vehicle license quota system. The primary justification for these policies includes encouraging substitution from GVs to EVs, reducing environmental issues related to GV usage, pushing the upgrading of the auto industry in China and building advantage in the international market. The primary justifications for these policies include encouraging the substitution of GVs with EVs and reducing environmental issues related to GV usage.

This paper examines how these two demand-side EV policies -EV subsidy and the green license plate policy- affect EV adoption in Beijing and evaluates whether these EV policies lead to net welfare gains, considering the expected environmental externalities. Specifically, I ask the following questions in this paper: How many additional EVs does each policy deploy on the road? How many gasoline vehicles (GVs) have been replaced by EVs due to these policies? How does the producers respond to these EV policies in pricing behavior? What's the welfare implications of these policies accounting for market distortions and environmental externalities?

To answer these questions, I estimate consumer demand for vehicles. However, there are two challenges. First, the green license plate policy which exempts EV consumers from a binding license quota policy requires consumers who choose EV license plates to pick their most preferred option from a limited choice set of eligible EV products instead of all available choice options (Berry, Levinsohn and Pakes, 1995). As a result, the observed sales of EVs depend not only on consumer preferences for vehicles products but also on the constraints of the choice sets imposed by the policy(Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022). To separately recover consumer preference for electric vehicles, consumer endogenous choices for license plate types should be considered in the demand estimation for vehicle products. Second, econometricians cannot observe consumer heterogeneous preference for EV products directly. However, accounting for consumer preference heterogeneity for EVs is essential for estimating consumer license plate choices and evaluating the effectiveness of EV policies in deploying EVs. For example, consumers with strong preference for EVs are more likely to apply for EV license plates. Buyers who value EVs would have purchased EVs even if there was no EV promotion policies (Xing, Leard and Li, 2021).

To address the above issues, I build a structural model that endogenizes consumers' preferences for license plate types and vehicle purchase decisions, allowing for consumer preference heterogeneity for EVs. On the demand side, I follow the framework of Berry, Levinsohn and Pakes (1995) and integrate consumer endogenous license plate choices as well as EV subsidy policy factors into the vehicle choice model. On the supply side, I assume automobile producers engage in a Nash-Bertrand pricing game.

With this structural model, I estimate the demand and for EVs and gasoline vehicles (GVs), and recover the distribution of consumer random tastes for EVs. 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 taste estimates for EVs and the resulting substitution patterns.

Model estimates suggest that, on average, consumers have a strong negative preference towards EVs. However, the variation in consumer taste for EV products is large, indicating consumers have significant heterogeneous preference towards EV products. To explore the substitution patterns between EVs and GVs, I examine the price elasticity based on the estimates. The results show that the average group-level cross-price elasticity between EV products is around 3.3555, suggesting strong substitution patterns within the EV product group. In contrast, the cross-price elasticity between EV products and GV products is only 0.0080, indicating limited substitution patterns between EVs and GVs during the sample period. This substitution pattern importantly is key for a cost-effectiveness analysis of the

EV policies.

To test the model implications and ensure there is sufficient variation to precisely estimate the policy impacts, I measure the effects of changes in EV policies on the total sales of EVs and GVs using a difference-in-differences (DID) framework. The DID analysis reveals that the sales volume of EVs increased by 227.1% after the local government announced the GLP policy and by 176.5% after the local subsidy was introduced during the sample period, while the sales of GVs did not change significantly. These findings reassure that in the structural model, parameters regarding the effects of EV policy factors can be precisely estimated by independent variation in consumers purchase decisions in response to the policies.

Using the estimated structural model, I infer product-level marginal cost from each automaker'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 subsidies and the green license plate policy.

Counterfactual analysis shows that there would have been only 1,193 EVs[1] sold during the sample period (2015) in Beijing under vehicle quota constraints if we removed both EV subsidies and the green license plate policy. In the context of vehicle quota constraints, there would have led to 2,465 more EVs sold if we implemented the GLP policy which provides EV buys distinctive license plate quotas. Introducing a subsidy program which offered each EV buyer $7,223 would have led to 2,174 additional EVs during the sample data period. Together, the combination of EV subsidies and the GLP policy resulted in 7,611 more EVs on the road in Beijing in 2015 suggesting the impacts of these two policies complement each other. These results shed light on the effectiveness of subsidy and the GLP policy on the EV adoption.

By studying the automakers' pricing responses to the EV policies on the supply side of my model, I find sizable impacts of the green license plate policy on the market power of EV automakers in the sample period in Beijing where there is only a few EV manufacturers competing in the market. This large impact could be driven by the fact that the GLP

[1] The counterfactual EV sales accounts for 0.32% among all vehicles sold.

policy separates GV and EV market and shields the EV producers from GV competitors. Consequently, there is a subsidy pass-through of 75% with the GLP policy compared to 99% without the GLP policy.

To further understand the welfare implications of these EV policies and consider the potential effects of the EV policies on the environmental externalities, I conduct a welfare impact analysis that accounts for the externalities resulting from vehicle usage, including carbon emissions, pollution, congestion, crashes, and space costs. The results highlight the critical role of environmental externalities in the welfare evaluations of EV policies. I find that, despite creating market distortions, imposing the GLP policy together with the license plate quota constraints could lead to net welfare gains as it significantly reduces externalities given certain assumptions on externalities estimates. The findings demonstrate the justification of the GLP policy which reserves EV quotas from the vehicle quota system from the perspective of reducing externalities.

For the reference of policymakers, I address two caveats warranted for the results in this paper. First, I do not model the network effect of EV adoption on the demand side, as the EV market was still in its early stages during the sample data period (2010-2015). For example, the relative share of EVs to GVs was around 0.24% in Beijing in 2015. As a result of the small EV user base, the network effect in my settings could be negligible. However, the indirect network effect due to an increasing number of EV users in the auto market may lead us to underestimate the policy impacts over time. Second, my model assumes static Nash-Bertrand pricing on the supply side. This assumption rules out EV technology spillovers, industry upgrading, and firms' dynamic pricing strategies. For example, firms may invest more in R&D of EV technology in response to EV adoption policies. In this case, EV policies could lead to larger positive impacts on market outcomes.

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 a novel perspective on the policy drivers behind the rapid growth of the EV market in large Chinese cities.

My findings of the substitution between gasoline cars and electric vehicles under subsidies and the GLP 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 model builds on a specific setting relating to earlier literature on the discrete choice model (Berry, Levinsohn and Pakes, 1995; Petrin, 2002) and latent choice constraints (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022). As detailed above, I develop a two-stage discrete choice model that incorporates consumer endogenous choices for license types into their vehicle decisions. This approach generalizes the discrete choice model by relaxing the assumption that consumers consider all available options.

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. My 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

Section 2.1 describes the two primary EV policies—EV subsidies and the GLP policy—in Beijing and discusses the background of EV adoption policies in China. For analysis, I compiled a dataset covering the years 2010 through 2015 in 11 cities (including Beijing) in China. This dataset includes market shares, vehicle characteristics, license application data, EV consumer survey responses regarding alternate "second choice" products, and consumer demographic information. Section 2.2 describes the data sources and presents basic descriptive information.

2.1 Policy Description

EVs have become a global trend and are considered a promising solution to environmental problems, including car emissions and air pollution caused by GV usage, by many policy-makers since the introduction of the first EV in the last decade. In China, the government affirmed its target to support the deployment of electric vehicles (EVs) among private car users in 2010. Driven by incentives for environmental sustainability and energy security, a series of EV policies have been implemented by both the central and local governments in major cities since 2010. These policies aim to encourage the substitution of GVs with EVs and reduce environmental issues related to GV usage.

2.1.1 Two Primary EV Policies in Beijing

Among these major cities, Beijing, one of the largest vehicle markets, implemented two primary demand-side EV policies to promote EV adoption.

Local EV Subsidies. The local municipal government in Beijing has initiated its local subsidy programs for electric vehicles (EVs) since 2010 to provide the financial incentives for EV buyers. In 2014-2015, the subsidy the local government provided to each eligible EV buyer is 45,000 RMB (7,223 USD), which accounts for 22.5% of average EV listed prices in the same period.

There were also other local subsidy programs varying across cities in terms of their timing and magnitude. For example, the Shanghai government offers a 30,000 RMB subsidy for EV and Plug-in EV purchases and a 40,000 RMB subsidy for EV purchases. Among these subsidy programs, the Beijing local government primarily targets battery EVs and provides the highest amount of local subsidies.

Green License Plate (GLP) Policy. In addition to the subsidy programs, the Beijing municipal government has established a separate license application system that offers additional license quotas for electric vehicle (EV) buyers under the binding license quota system[1]. This quota-related EV policy is known as the green license plate policy in China (referred to as the GLP policy in this paper) because the government offers distinctive green-colored license plates (with regular license plates being blue) to EV license applicants.

Though the GLP policy also set a quota for the EV license system, it was not binding most of the time. It exempted EV buyers from the stringent license quota system for regular license plates in Beijing. According to the official website of the Beijing Transportation Bureau, the winning odds of an EV license plate were 100% in February 2014, while the winning odds of a regular license plate were only 0.903% during the same period. The GLP policy in Beijing offered an easy and convenient way for EV buyers to obtain a license plate and significantly shortened the waiting periods for a new EV license plate compared to the complex and binding regular license lottery system, which could provide substantial incentives for EV ownership (Li et al., 2020).

Appendix A summarizes the timeline of EV policies in the seven major cities in China. In this paper, I focus on the impacts of local subsidies and the green license plate policy in the context of Beijing.

2.1.2 Background of EV Adoption Policies

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

[1]The license quota system is a policy to cap the number of new-registered vehicles through a quota allocation system. It has been adopted in seven cities in China to limit vehicle usage since 2010. Details can be found in Section 2.1.2 and in previous studies (Li 2018, Guo and Xiao 2022).

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%. 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. **Central Subsidy.** The Chinese central government 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 during 2010-2014. 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. These central subsidies were also included in my study and kept constant in the analysis.

License Quota Systems. 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 win-

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

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

ning 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).

2.2 Data

My analysis relies on five main data sets.

The first data set I use comes from Chinese vehicle registration records covering all registered vehicles in 11 cities in China, including provincial capital cities (e.g. Beijing) or municipalities, over the period of 2010-2015. I compiled the registration records into quarterly trim-level vehicle sales in each market defined as a city in a given quarter. Each observation in the data set represents a product-level vehicle model in one market.

The second data set applied in my analysis is the product information data, which also comes from Chinese vehicle registration records. 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 my analysis involves the license application information. I collect the data 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 regular license 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. Note that the lottery license allocation in Beijing happens monthly or bi-monthly in Beijing, I aggregate the quota and applicants numbers into quarterly data.

The fourth data source is microdata on EV consumers' second-choice preferences in 2015, obtained from the China Electric Passenger Vehicle Consumer Survey Report (2015). This data provides the average share of EV consumers in China who would still choose EVs if their current EV choice were unavailable in 2015.

The fifth data set I rely on is the aggregate household information sourcing from China's national household survey. It includes the total number of population 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.

3 Effects of EV Subsidy Programs and the GLP Policy

To check whether the GLP policy affect EV sales, I first investigate the dynamic impacts of the GLP policy on the quarterly sales of EVs and GVs with an event study design. The specification is as follows:

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

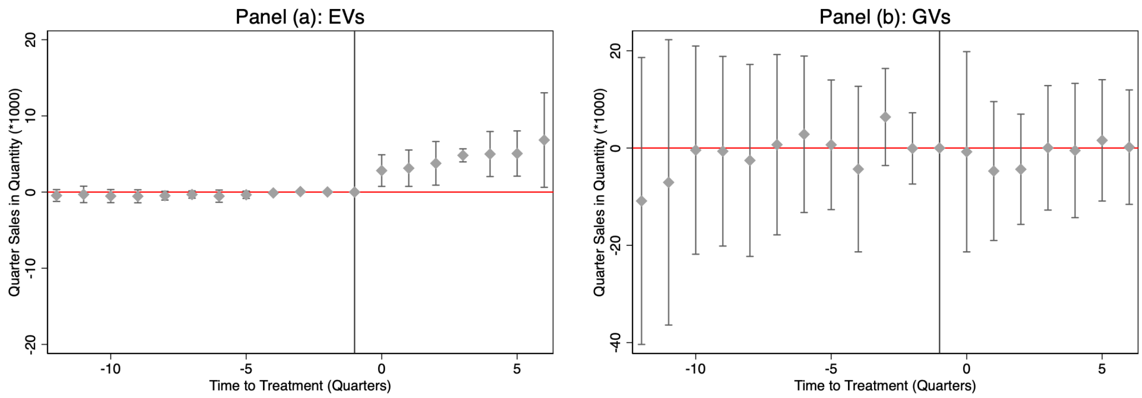
where Y_{gmt} denotes the outcome measure for group g (EVs or GVs), defined as the total number of sales in city m at quarter-year t. G_m is an indicator variable that equals 1 for the treatment cities (e.g., Beijing) and 0 for the control cities. T_k is an indicator variable for the k^{th} quarter-year relative to the implementation time of the green license plate policy. X_{gmt} represents a vector of control variables, including subsidies, the total number of quotas, and the total number of vehicle models in city m at time t. $\eta_{m\times year}$ and η_t denote the city-year and quarter-year fixed effects, respectively. ξ_{gmt} is the error term.

In the event study, the coefficients of interest are a_k, representing a series of interaction terms between the treatment city indicator and quarter-year dummies. The analysis extends from 11 quarters before to 6 quarters after the policy implementation.

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). I 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 GLP policy. Following the implementation of the GLP 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 in the treatment cities increased by $4,514$ on average in each quarter. The sales of GVs did not show significant changes after the green license policy.

In addition to the event study analysis, I investigate the impacts of EV subsidy and the

Figure 1: Effect of the GLP Policy on Total Sales: Event Study



***Notes**: The figure shows the effect of the GLP policy on total quarterly sales of EVs and GVs in China during 2010-2015. It 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. The number of observations is 2,448.*

GLP policy on the total sales of EVs and GVs using the difference-in-differences framework. The specification is as follows:

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

where Y_{gmt} is the outcome measure of sales for group g (EVs or GVs) in city m during month-year t. G_{mt} is an interaction indicator for the treatment cities with the GLP policy, taking the value 1 if city m implemented the green license policy during or after month-year t, and 0 otherwise. D_{mt} is an interaction indicator for the treatment cities with local subsidies, equal to 1 if city m started the local subsidy program during or after month-year t, and 0 otherwise. X_{gmt} is a vector of control variables, including indicators for license quota limits, the total number of available products in group g, and a constant. City and month-year fixed effects are included in the regression through the terms η_m and η_t, respectively. The coefficients b_1 and b_2 capture the impacts of the GLP policy and EV subsidies on the sales of the group (EVs or GVs), respectively. The larger the coefficients b_1 and b_2, the stronger the impacts of the relevant policies on the sales of EVs and GVs, holding all other variables constant.

Following the specification in equation 2, I present the regression results in Table 1. The dependent variables in Columns (1) and (2) are the logarithms of the total number of monthly EV and GV sales, respectively. Here, $(e^{b_1}-1)$ and $(e^{b_2}-1)$ provide the percentage

Table 1: DID Regression Results

Quantitative Effects	(1)	(2)
	EV	GV
	ln(sales)	ln(sales)
Average Effects of the GLP Policy (b_1)	1.186***	-0.193
	(0.374)	(0.109)
Average Effects of EV Subsidy (b_2)	1.017**	0.0212
	(0.389)	(0.0401)
No. of Products	0.926***	0.00241***
	(0.115)	(0.000445)
City fixed effect	YES	YES
Month-Year fixed effect	YES	YES
R-squared	0.795	0.939
Obs.	2,448	2,448

***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. The treatment cities include Beijing, Tianjin, Shanghai, Hangzhou, Guangzhou and Shenzhen.*

change in the sales observed after the local government announced the GLP policy and the subsidy program, holding all other variables constant.

As the benchmark specification in my analysis, the coefficient estimate in Column (1) for the green license plate policy (b_1) is 1.186, suggesting that average EV sales increased by 227.1% after the government announced the GLP policy, with all other variables controlled. The coefficient estimate for the EV subsidy program (b_2) is 1.017, indicating that total monthly EV sales increased by 176.5% after the local subsidy program was introduced. The magnitudes of the coefficients b_1 and b_2 in Column (1) demonstrate the substantially positive impacts of the GLP policy and subsidies on EV sales. As indicated by Column (2), the impacts of the GLP policy and the EV subsidy program on GV sales are insignificant.

Threats to Identification. One concern regarding the robustness of the results is the assumption of a constant average treatment effect across group over time. There may be heterogeneous treatment effects of the policies across the multiple treatment cities over time. To alleviate the concern, I test the compositional changes in the treatment cities and check the new estimator proposed by de Chaisemartin and D'Haultfœuille (2020). The results are consistent suggesting significant positive impacts of the GLP policy and EV subsidies on EV adoption. Besides, there are concerns about the network externalities of EV charging stations. For example, the construction of charging stations may bring positive network effects to the development of the EV market which leads to over estimation of the EV policy impacts. However, in this study, the network effects of EV charging piles may not be a major concern as home charging of EVs is one of the primary charging method in the sample period (2010-2015).

The reduced-form evidence show the impacts of both EV policies on the total sales of EVs and GVs. Yet, to study how EV policies affect consumer and firm behavior and welfare, a structural model is necessary for policy analysis.

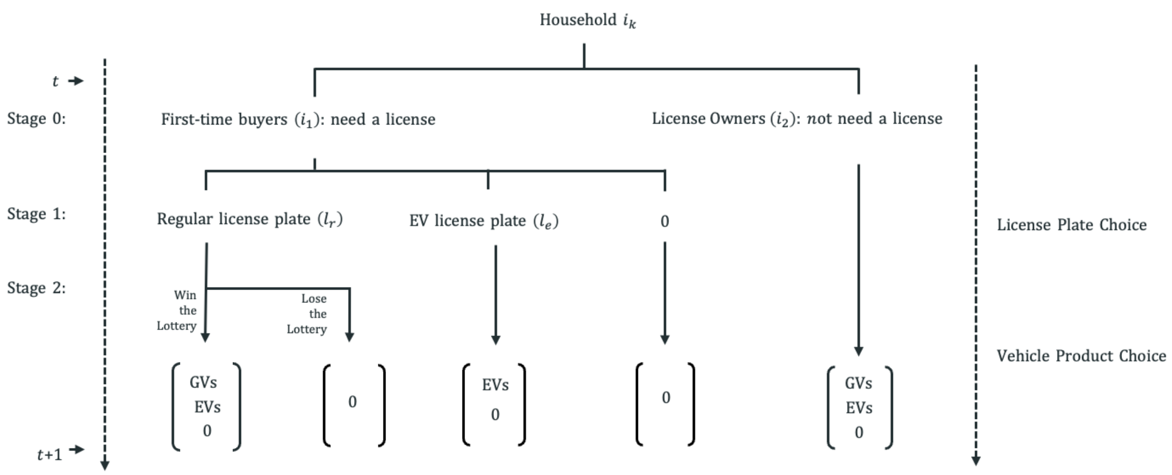
4 Structural Model

In this section, I develop a structural model to explain the policy impacts through consumer and firm responses. The model includes a discrete choice system which endogenizes consumer license plate choice as well as consumer vehicle choice incorporating consumers taste heterogeneity towards EVs on the demand side following the framework of Berry, Levinsohn and Pakes (1995). I then explain the firm responses with a Nash-Bertrand pricing game model on the supply side.

4.1 Demand Side

The timing of the model on the demand side is displayed in Figure 2. The model is illustrated in details as following:

Figure 2: Model Timeline



License Ownership (Stage 0). Stage 0 depicts the nature of the market. At **stage 0**, there are two types of consumers in the population with a total size of M_{mt} in the market m at time t. They are first-time consumers i_1 and license owners i_2. I assume that consumers are drawn from the same population in the market and there is no dynamics choices among the consumers in the market m at time t. That is, consumers go through the model process in each market with no memory of the past choices.

For a first-time consumer i_1, she does not have a car nor a license plate at the time when the quota policy is implemented. She needs to acquire a new license plate under the quota system in Stage 1 to register a new vehicle in Stage 2.

For a license owner i_2, she owns a car and a license plate at the time when the quota system is implemented. Under the quota policy, she can scrap her used vehicle[1] and use

[1]Note that a license plate cannot be transferred or resale to others given the quota policy.

the old license to register a new vehicle. She does not need to acquire a new license plate to register her car, thus she could skip the decision process in Stage 1 with a regular license plate. She could make her choice of vehicle produces in Stage 2 with the full choice set denoted as $\{0, \mathcal{J}_{GV}, \mathcal{J}_{EV}\}$ where $\mathcal{J}_{GV}$ represents the set of all available GVs. $\mathcal{J}_{EV}$ is the set of all available EVs. 0 denotes the option of no purchase.

Note that the two groups of consumers cannot be distinguished because we cannot observe individual-level data and therefore cannot identify the type of households. Following the approach of Li (2018), I assume the vehicle ownership rate, denoted by o_{mt}, equals the probability of being a license owner in market m at time t. Here, o_{mt} is the ratio of total vehicle (license) owners in market m at time t to the total number of households in market m at time t. While this assumption may seem restrictive, it closely reflects reality because the quota policy implementation in Beijing is an exogenous shock to consumers.

Given this assumption, the consumer type in the model can be derived from a Bernoulli distribution, with a probability of $(1 - o_{mt})$ of being a first-time buyer (i_1) and a probability of o_{mt} of being a license owner. It is written as

$$Pr_{i_k mt} = \begin{cases} 1 - o_{mt} & \text{if} \quad k = 1, \\ o_{mt} & \text{if} \quad k = 2. \end{cases} \tag{3}$$

Since I solve consumer choice model via a backward induction method, I will present the following parts of the model starting from consumer vehicle choice in Stage 2 and then move to consumer license plate choice in Stage 1.

Stage 2: Consumer Choice for Vehicles

Stage 2 models consumer choices for vehicles following the framework of Berry, Levinsohn and Pakes (1995) and Grigolon and Verboven (2014). At Stage 2 of time t, first-time consumers know whether they have won or lost the lottery through the license plate application. Both first-time consumers and license owners then make their vehicle purchase decisions by choosing their most preferred car model j from their choice set.

I model the indirect utility $u_{i_k jmt}$ of consumer i_k ($k = 1, 2$) for vehicle product j in market m at time t as follows:

$$u_{i_k jmt} = \underbrace{\delta_{jmt} + \mu_{i_k jmt}}_{\bar{u}_{i_k jmt}} + \epsilon_{i_k jmt}, \tag{4}$$

where i_k represents a first-time consumer if $k = 1$ or a license owner if $k = 2$.
- δ_{jmt} denotes the mean utility of product j in market m at time t.
- $\mu_{i_k jmt}$ is the heterogeneous utility of consumer i_k for product j in market m at time t.
- $\bar{u}_{i_k jmt}$ represents the sum of the mean utility term and the heterogeneous utility term.
- $\epsilon_{i_k jmt}$ is an idiosyncratic consumer-vehicle specific term that follows a type I extreme value distribution.

In the model, I assume that the product-specific preference shock $\epsilon_{i_1 jmt}$ is realized for a first-time consumer after they have made their license plate type choice in Stage 1.

I further specify the mean utility function δ_{jmt} of consuming product j in market m at time t as

$$\delta_{jmt} = \bar{\alpha}(p_{jmt} - d_{jmt}) + \bar{\kappa} I_{j\in\mathcal{J}_{\text{EV}}} + x_{jmt}\beta + \eta_m + \eta_t + \xi_{\text{make}} + e_{jmt}, \tag{5}$$

where $(p_{jmt} - d_{jmt})$ is the subsidized price that consumers pay for product j in market m at time t. p_{jmt} is the label price adjusted for tax for product j in market m at time t. d_{jmt} is the total amount of subsidy rebate for product j in market m at time t offered by the government. It takes the value of d_{jmt} if product j is an EV eligible for the subsidy and 0 otherwise. $I_{j\in\mathcal{J}_{\text{EV}}}$ is an indicator for EVs, equal to 1 if $j \in \mathcal{J}_{\text{EV}}$ and 0 otherwise. x_{jmt} is a vector of observed product characteristics, including vehicle length, weight, width, and power. η_m and η_t capture the city-specific and time-specific preferences for vehicles, respectively, controlling for common demand shocks and seasonality across cities. ξ_{make} represents make-level unobserved product attributes, including quality and safety features not captured by the observed product characteristics. e_{jmt} represents demand shocks that vary across time and market.

The heterogeneous utility $\mu_{i_k jmt}$ of consumer i_k is defined as:

$$\mu_{i_k jmt} = \sigma_{EV} \nu^{EV}_{i_k mt} I_{j\in\mathcal{J}_{\text{EV}}} + \gamma_1 I_{k=1}, \tag{6}$$

where $I_{j\in\mathcal{J}_{\text{EV}}}$ is an indicator for EVs, equal to 1 if $j \in \mathcal{J}_{\text{EV}}$ and 0 otherwise. $\nu^{EV}_{i_k mt}$ captures the unobserved consumer attributes for the EV characteristic that has a standard normal distribution with the standard deviation to be σ_{EV}. It incorporates consumer heterogeneity towards EVs and allows for more flexible substitution patterns. $I_{k=1}$ is an indicator for first-time consumers, equal to 1 if $k = 1$ and 0 otherwise. γ_1 captures a consumer type-specific utility difference between first-time buyers ($k = 1$) and license owners ($k = 2$). The parameter γ_1 address the fact that the utility of a first-time consumer i_1 choosing no purchase option could be different from that of a license owner i_2. It is because first-time consumers in Stage 2 are supposed be more determined to purchase a vehicle after she went through the license application process. γ_1 is identified from the variations between predicted shares of no purchase options in Stage 2 and the observed shares of no purchase among the license winners. I assume that the first-time consumers and license owners have the same preference parameters except the consumer type-specific parameter γ_1[1].

Stage 1: Choice for License Types

Stage 1 models consumer choices for the license plate type and captures how the quota system and green license plate policy work. At Stage 1 of time t, a first-time buyer (i_1) who does not own a license plate will go through the license application process under the quota policy. With the GLP policy, she has three options to choose from - applying for a regular license and participate in the lottery allocation process, applying for an EV (green) license plate, or choosing no purchase[2]. I 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 option of no purchase.

To capture the fact that the GLP policy requires EV license plate applicants to choose among EV models, my model assumes first-time consumers' license plate type choice in Stage 1 constrains their vehicle choice set in Stage 2. More specifically, if she chooses a regular license plate and wins the lottery, then she could choose from the full choice set given by $\{0, \mathcal{J}_{\text{GV}}, \mathcal{J}_{\text{EV}}\}$. If she chooses a regular license plate but loses the lottery, then her

[1]There may be concerns about the validity of this assumption. For example, the two types of consumers may differ in income distributions or taste distributions given their previous vehicle ownership status. My model is flexible to incorporates these features if more consumer-level information is available.

[2]Without the GLP policy, she has only two options - applying for a regular license and participate in the lottery allocation process or choosing no purchase

vehicle choice set is limited to be $\{0\}$. If the consumer i_1 chooses a EV license plate (l_e) in Stage 1, then she could get a EV license plate through the GLP policy associated with a constrained choice set of vehicle models given by $\{0, \mathcal{J}_{EV}\}$. The relationship between the license plate type choice in Stage 1 (l_{i_1})and the vehicle choice set ($\Omega_{l_{i_1}}$) in Stage 2 can be written as:

$$\begin{aligned} i_1 \text{ chooses a regular license plate} \quad (l_{i_1} = l_r) &\implies \Omega_{l_r} = \{0, \mathcal{J}_{\text{GV}}, \mathcal{J}_{\text{EV}}\}, \\ i_1 \text{ chooses a EV license plate} \quad (l_{i_1} = l_e) &\implies \Omega_{l_e} = \{0, \mathcal{J}_{\text{EV}}\}. \end{aligned} \tag{7}$$

Given the setup that consumer's license plate type choice corresponds their vehicle choice set and the fact that there is no additional value of owning a license plate[1], I write the value $V_{i_1 lmt}$ for a first-time consumer i_1 obtaining the license plate of type l in market m at time t as

$$V_{i_1 lmt} = \ln\Big[\sum_{j \in \Omega_l} \exp(\delta_{jmt} + \mu_{i_1 jmt})\Big], \tag{8}$$

where $V_{i_1 lmt}$ denotes the ex ante value of obtaining the preferred license type l as opposed to holding the outside option. It is assumed to be the logit inclusive value of all the available options in the vehicle choice set Ω_l given by the license plate type l. The relationship between the license plate choice l and the vehicle choice set Ω_l is depicted in equation (7). δ_{jmt} and $\mu_{i_1 jmt}$ denote the mean and heterogeneous utility of consumer i_1 consuming product j in the market m at time t.

A note on the assumption and functional form of consumer's valuation on the license plate type is in order. First, I assume consumers choose which license plate to apply based on the utility of all available options in the vehicle choice set, which are determined by a set of vehicle products they can purchase rather than a specific product. The setup is valid in my model given the timing of events. Specifically, a consumer makes their license plate type choice in Stage 1 before their individual product-specific taste shock for each vehicle $\mu_{i_1 jmt}$ is realized. Therefore, they consider all available options in the vehicle choice set rather than the most preferred choice, to determine their valuation for each license plate type. This assumption, though non-trivial, is not as restrictive as it appears. It is consistent

[1]Resale or transfer of license plates is not allowed.

with common purchase behavior, where consumers choose among a group of car models (e.g. EVs) before selecting a specific vehicle model.

Second, the idea of taking the logit inclusive value of the corresponding vehicle choice set as the value for a license plate type l is inspired by Gowrisankaran and Rysman (2012). The functional form of the logit inclusive value captures consumers' endogenous selection for license plate type choice given their heterogeneous preference. For example, the model allows for the observed fact that consumers who prefer EVs are more likely to choose EV license plates, and thus will self select to participate in the EV license application process.

It is important to mention that this assumption for consumers' valuation for license plate types 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. The functional form of the logit inclusive value also facilitates identification and estimation in the following parts of this paper by: 1) allowing us to identify consumers' valuations for the license plate type V_{i_1lmt} from their vehicle preferences in Stage. 2) simplifying the decision process of license plate types to be the trade-offs between the expected valuation of the relevant choice set and the expected cost of applying for the type l license plate.

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

$$U_{i_1lmt} = \underbrace{E_{mt}[V_{i_1lmt}] - c_l}_{\bar{U}_{i_1lmt}} + \epsilon_{i_1lmt}, \tag{9}$$

where $E_{mt}[V_{i_1lmt}]$ denotes the expected utility from obtaining a license plate of type l in market m at time t. It takes the functional form as:

$$E_{mt}[V_{i_1lmt}] = \underbrace{\rho_{lmt}}_{\text{expected winning odds of license type } l} \times \underbrace{V_{i_1lmt}}_{\text{value of the license type } l}, \tag{10}$$

where ρ_{lmt} is the expected winning odds of the license type l in the market m at time t. V_{i_1lmt} is the consumer's valuation of obtaining a license plate of type l in market m at time t. In equation (9), c_l in captures the cost of obtaining the license plate l that is observed by the consumers but not the econometricians. It is interpreted as the financial and opportunity cost of participating in the complex application procedure. The identification of the cost parameter comes from variations in observed shares of consumers choosing each type of license type and the option of no purchase in market 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 $U_{i_1 0mt} = 0$.

Given the quota and lottery application policy, the expected winning odd $\hat{\rho}_{lmt}$ is defined as

$$\rho_{lmt} = \min\left\{\frac{q_{lmt}}{Q_{lmt}}, 1\right\}, \tag{11}$$

where q_{lmt-1} is the total number of quotas for the license plate l set by the policymakers in the market m at period t. Q_{lmt} is the total number for applicants in the market m at period t. 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 $\frac{q_{lmt}}{Q_{lmt}}$ if the quota system is binding. This setup is flexible to capture unexpected policy changes in the quota system[1]. Here, I assume consumers have rational expectations over the winning odds of license plates. Also, the participation of a single consumer does not affect the expected winning odds.

Aggregate Demand

Vehicle choice probabilities. Based on the i.i.d. type I extreme value distribution of $\epsilon_{i_k jmt}$, the choice probability of consumer i_k for product j conditional on winning the license type l is

$$Pr_{i_k jmt}(p_{jmt}, d_{jmt}, X_{jmt}, \xi_{jmt}, Z_{i_k jmt} | l_{i_k} = l, \text{win}) = \frac{\exp(\delta_{jmt} + \mu_{i_k jmt})}{\sum_{j \in \Omega_{l_{i_k}}} \exp(\delta_{jmt} + \mu_{i_1 jmt})}, \tag{12}$$

where $Z_{i_k jmt}$ includes unobserved consumer heterogeneous taste $\mu^{\text{EV}}_{i_k mt}$ that affects consumer preference towards EV characteristic and the unobserved consumer type-specific utility γ_1 that affects first-time consumer's preference on the option of no purchase. $\Omega_{l_{i_k}}$ is the vehicle choice set constrained by the license plate choice l_{i_k} given by the equation (7). Note that a license owner i_2 does not go through the license application process in Stage 1 as they've had a regular license plate. For the consistency of notation, I denote the license plate type of i_2 as $l_{i_2} = l_r$ with the full vehicle choice set $\Omega_{l_r} = \{0, \mathcal{J}_{GV}, \mathcal{J}_{EV}\}$.

[1] E.g. Beijing unexpectedly announced free EV license plates to all EV license applicants in the EV lottery in Oct, 2015.

License plate choice probabilities. Based on the i.i.d. type I extreme value distribution of $\epsilon_{i_k lmt}$, the choice probability of first-time consumer i_1 for license plate l is

$$Pr_{i_1 lmt}(p_{jmt}, d_{jmt}, X_{jmt}, \xi_{jmt}, Z_{i_k jmt}, c_l, \rho_{lmt}) = \frac{\exp(\overline{U}_{i_1 lmt})}{1 + \sum_{l \in \{l_r, l_e\}} \exp(\overline{U}_{i_1 lmt})}, \tag{13}$$

where ρ_{lmt} is the winning odds of the license plate l in market m at time t defined in equation (11). $\overline{U}_{i_1 lmt}$ is the expected utility of consumer i_1 obtaining the license plate l that captures consumer's preference for all the available options corresponding to the license choice l as well as the cost of obtaining the license plate l. For the consistency of notation, the license plate choice probability of a license owner i_2 is written as $Pr_{i_2 lmt}(l_{i_2} = l_r) = 1$.

With the choice probabilities, I generate the aggregate sales of product j in market m at t. Under the quota system and the GLP policy, the market share s_{jmt} of product j is given by

$$s_{jmt} = \int \mathbf{Pr}_{i_k jmt}(.|l_{i_k}, \text{win}) \times \mathbf{Pr}_{i_k lmt}(.) dF(Z_{i_k jmt}, \rho_{lmt}, i_k), \tag{14}$$

where $\mathbf{Pr}_{i_k jmt}(.|l_{i_k}, \text{win})$ is the vehicle choice probability given by equation (12). $\mathbf{Pr}_{i_k lmt}(.)$ denotes the license plate choice probability given by equation (13).

To explain the policy impacts, I decompose the aggregate market shares of product j in equation (14) into three parts[1]:

$$\begin{aligned} s_{jmt} = & \underbrace{\int [\mathbf{Pr}_{i_1 jmt}(.|l_{i_1} = l_r, \text{win}) \times \mathbf{Pr}_{i_1 l_r mt}(.) \times \rho_{l_r mt} \times \mathbf{Pr}_{i_1}] dF(Z_{i_1 jmt})}_{\text{(i) shares from first-time consumers } i_1 \text{ who win the regular license plate lottery}} \\ & + \underbrace{\int [\mathbf{Pr}_{i_1 jmt}(.|l_{i_1} = l_e, \text{win}) \times \mathbf{Pr}_{i_1 l_e mt}(.) \times \rho_{l_e mt} \times \mathbf{Pr}_{i_1}] dF(Z_{i_1 jmt})}_{\text{(ii) shares from first-time consumers } i_1 \text{ who choose the EV license plate}} \\ & + \underbrace{\int [\mathbf{Pr}_{i_2 jmt}(.|l_{i_2} = l_r) \times \mathbf{Pr}_{i_2 l_r mt}(.) \times \mathbf{Pr}_{i_2}] dF(Z_{i_2 jmt})}_{\text{(iii) shares from license owners } i_2 \text{ who own regular license plates}}, \end{aligned} \tag{15}$$

where Pr_{i_1} and Pr_{i_2} are the type probabilities of being first-time consumers or license owners, respectively, as defined in equation (3).

As illustrated above, the model specification incorporate consumer heterogeneous taste into the heterogeneous utility term $\mu_{i_k jmt}$ in consumer vehicle choice in Stage 2. It also

[1] Appendix D decomposes the market shares for the option of no purchase.

endogenizes consumer license plate choice through the term for consumer's valuation of license plate types - $V_{i_1 lmt}$. As for the policies, the model incorporates the license quota system, the GLP policy through the quota numbers defined in the lottery winning odds of license plates in equation (11) and integrate the factor for subsidy amounts into consumer perceived prices in equation (5). Especially, the GLP policy implemented in Beijing during the sample period allows unbinding EV license quotas and leads to the winning odds $\rho_{l_e mt}$ of a EV license plate to be 100%.

4.2 Supply Side

On the supply side, I assume auto manufacturers indexed by f play a static Nash-Bertrand pricing game in each market m at time t following Berry, Levinsohn and Pakes (1995) and Nevo (2000). Manufacturers simultaneously choose the price for all the vehicle models $\mathcal{J}^f_{mt}$ of their firm to maximize firm profit. Observed prices form a Nash equilibrium to the pricing game. 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 each firm f is:

$$\max_{\{p_{jmt}\}_{j \in J^f_{mt}}} \pi_{fmt} = \sum_{j \in \mathcal{J}^f_{mt}} (p_{jmt} - mc_{jmt}) s_{jmt} M_{mt}, \tag{16}$$

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

The pricing first-order condition for vehicle j is:

$$s_{jmt} + \sum_{k \in J^f_{mt}} (p_{jmt} - mc_{jmt}) \frac{\partial s_{jmt}}{\partial p_{kmt}} = 0. \tag{17}$$

Rearranging the first-order conditions, I can solve for the marginal cost mc_{jmt} for each product j and use the estimated marginal costs for the counterfactual analysis.

My assumption of Nash-Bertrand pricing rules out the dynamic decisions of firms (e.g., entry or exit decisions) and changes in firms' strategies over time. If firms employ strategies beyond maximizing their current profit, the implied marginal costs inferred by assuming a static Nash equilibrium in prices could be misleading. Alternative assumptions for firms' objective functions could be incorporated in further counterfactual analysis. However, in this study, I focus on evaluating demand-side policies and do not attempt to measure supply-side dynamics as in Bresnahan (1987) and Guo and Xiao (2022).

4.3 Remarks on Policy Effects

The structural model features the following channels through which the EV policies could affect the market outcomes of EVs and GVs:

(i) *direct price effects*. My model depicts the EV subsidy impacts by including the subsidy amount parameter d_{jmt} in the mean utility equation (5) in the demand side. The change in the EV subsidy amount affects consumer perceived prices for vehicles, and thus affect the market outcomes of EVs.

(ii) *quota effects.* In the two-stage discrete choice model, quota policies, including constraints on regular license plates and the GLP policy for EV license plates, are captured through the variable of quota number q_{lmt} in the license plate winning odds' equation (11) and in the aggregate demand equation (14) on the demand side. Changes in the quota numbers for regular or EV license plates can lead to shifts in consumer license plate choices in Stage 1, which subsequently affect consumer vehicle purchase decisions in Stage 2.

(iii) *substitution effects.* The structural model captures the substitution patterns between EVs and GVs. Changes in EV policies could affect the market outcomes of both EVs and GVs through the embedded substitution patterns in the model.

(iv) *prices adjustment effects.* The supply side of the structural model allows EV and GV producers to adjust prices in response to the changes in EV policies. For example, the GLP policy could potentially grant EV manufacturers greater market power to set higher prices as it separates the EV market from the GV market.

With the model estimated, I can reveal consumers heterogeneous taste towards EVs, the substitution patterns between EVs and GV, and examine to what extent the demand-side government policies affect the market outcomes of EVs and GVs.

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.

5.1 Estimation Method

The goal of my estimation is to recover three sets of parameters in the model. I denote them as $(\theta_1, \theta_2, \theta_3)$, where θ_1 includes the mean preference parameters for vehicle characteristics in the mean utility equation (5) written as $\theta_1 = \{\bar{\alpha}, \bar{\kappa}, \beta, \eta_m, \eta_t, \xi_{\text{make}}\}$. θ_2 represents the set of heterogeneous taste parameters in the consumer-specified utility equation (6) written as $\theta_2 = \{\sigma^{\text{EV}}, \gamma_1\}$. θ_3 denotes the set of cost parameters of obtaining the regular and EV license plate defined in equation (9) written as $\theta_3 = \{c_{l_r}, c_{l_e}\}$.

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). My estimation procedure is implemented in the following 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 utilities $\boldsymbol{\delta}$ towards all products where $\boldsymbol{\delta} = \{\delta_j\}_{\mathcal{J}}$, consumer heterogeneous preference parameters θ_2 and consumers' license application costs θ_3 to recover the set parameters $\Theta = (\boldsymbol{\delta}, \theta_2, \theta_3)$. In the estimation procedure, I rely on three sets of moments.

Moment 1. I employ the first set of moments from the second-choice information in the China Electric Passenger Vehicle Consumer Survey Report (2015).

I construct the second-choice micro-moments by matching the observed and predicted shares of EV consumers who choose EVs as their second choice, conditional on their current choice being unavailable. This set of micro-moments is crucial for identifying consumer preference heterogeneity for EVs.

From the microdata, the observed share $S_{\text{second choice as EVs|EV buyers}}$ of EV consumers who would choose an EV as their second choice is given by

$$S_{\text{second choice as EVs|EV buyers}} = \widehat{I_{h \in \mathcal{J}_{EV} \setminus j | j \in \mathcal{J}_{EV}}}, \tag{18}$$

where $I_{h\in\mathcal{J}_{EV}\setminus j|j\in\mathcal{J}_{EV}}$ is an indicator function that equals 1 if an EV consumer, whose most preferred product is $j \in \mathcal{J}_{\mathrm{EV}}$, would still choose an EV product $h \in \{\mathcal{J}_{\mathrm{EV}} \setminus j\}$ given that their current choice j is not available.

From the model, the predicted share $\tilde{\mathrm{S}}_{\text{second choice as EVs|EV buyers}}$ of EV consumer's second choice as EVs is a function of observed variables and the parameter set Θ given by:

$$\tilde{\mathrm{S}}(\Theta)_{\text{second choice as EVs|EV buyers}} = \frac{\sum_{j\in\mathcal{J}_{\mathrm{EV}}}\sum_{h\in\{\mathcal{J}_{\mathrm{EV}}\setminus j\}} s_{h,j}}{\sum_{j\in\mathcal{J}_{\mathrm{EV}}} s_j}, \tag{19}$$

where h and j denote the product. s_j is the aggregate shares of product j given by equation (14). $s_{h,j}$ represents the aggregate shares of consumers jointly choosing product h as second preferred option and product j as the most preferred option computed from the model. It is written as

$$s_{h,j}(\Theta) = \int \mathcal{P}r_{i_k hj}(\Theta, Z_{i_k j}|l_{i_k}, \mathrm{win}) \times \mathbf{Pr}_{i_k l}(\Theta) dF(Z_{i_k j}, \rho_l, i_k), \tag{20}$$

where $\mathbf{Pr}_{i_k l}(.)$ is the license choice probabilities given by equation (13). $\mathcal{P}r_{i_k hj}(.|l_{i_k}, \mathrm{win})$ is the joint choice probability of second-preferred product h with most preferred product j conditional on winning the license plate choice l_{i_k}. Without loss of generality in the estimation, I compute the joint choice probabilities $\mathcal{P}r_{i_k hj}(.|l_{i_k}, \mathrm{win})$ of products $h \in \mathcal{J}_{\mathrm{EV}}, j \in \mathcal{J}_{\mathrm{EV}}$ as

$$\mathcal{P}r_{i_k hj}(\Theta, Z_{i_k j}|l_{i_k}, \mathrm{win}) = \frac{\exp(\bar{u}_{i_k h})}{\sum_{h\in\{\Omega_{l_{i_k}}\setminus j\}} \exp(\bar{u}_{i_k h})} \cdot \frac{\exp(\bar{u}_{i_k j})}{\sum_{j\in\Omega_{l_{i_k}}} \exp(\bar{u}_{i_k j})} \tag{21}$$

Here, $\bar{u}_{i_k h}$ represents the deterministic utility for product h give by the sum of mean utility δ_h and heterogeneous utility $\mu_{i_k h}$.$\Omega_{l_{i_k}}$ denotes the vehicle choice set constrained by the license choice l_{i_k}. For consistency, I denote the license plate type of license owner i_2 as $l_{i_2} = l_r$.

Then the first set of micro-moments is given by

$$g_1(\Theta) = \mathbb{E}_{\mathfrak{t}}\big[\mathrm{S}_{\text{second choice as EVs|EV buyers}} - \tilde{\mathrm{S}}(\Theta)_{\text{second choice as EVs|EV buyers}}\big]. \tag{22}$$

Moment 2. The second set of micro-moment conditions is constructed based on the observed shares of no purchase among winners of regular license plate from the license application information. This helps identify the consumer type-specific heterogeneity parameter. I match the predicted shares of no purchase options among winners of regular license plate to their empirical analogues observed in the data and formulate the moment conditions as

$$g_2(\Theta) = \mathbb{E}_t\big[\mathrm{S}_{0|i_1,\text{win } l_r} - \tilde{\mathrm{S}}(\Theta)_{0|i_1,\text{win } l_r}\big], \tag{23}$$

where $\mathrm{S}_{0|i_1,\text{win } l_r}$ is the observed shares of no purchase among winners of regular license plate. $\tilde{\mathrm{S}}(\Theta)_{0|i_1,\text{win } l_r}$ is the predicted shares of no purchase options among winners of regular license plate as a function of Θ.

The observed shares $\mathrm{S}_{0|i_1,\text{win } l_r}$ of no purchase among the regular license winners are calculated as the number of unused license quotas in market m at time t divided by the total number of regular license plate winners (equal to the quota number) in market m at time t. Note that license plate winners have a six-month activation period to confirm their plate number and register their vehicle in Beijing. A license quota is marked as unused only if the winners do not register a vehicle by the end of the activation period.

The predicted shares $\tilde{\mathrm{S}}(\Theta)_{0|i_1,\text{win } l_r}$ are computed as the aggregate shares of not purchasing a vehicle, conditional on a first-time consumer winning the regular license plate. The expression is given by

$$\tilde{\mathrm{S}}(\Theta)_{0|i_1,\text{win } l_r} = \int \mathbf{Pr}_{i_1 0}(\Theta, Z_{i_1 j} | l_{i_1} = l_r, \text{win}) dF(Z_{i_1 j}), \tag{24}$$

where $\mathbf{Pr}_{i_1 0}(\Theta, Z_{i_1 j} | l_{i_1} = l_r, \text{win})$ is the choice probability of not purchasing a vehicle conditional on winning the regular license written as

$$\mathbf{Pr}_{i_1 0}(\Theta, Z_{i_1 j} | l_{i_1} = l_r, \text{win}) = \frac{1}{1 + \sum_{j \in \{\mathcal{J}_{\text{GV}}, \mathcal{J}_{\text{EV}}\}} \exp(\bar{u}_{i_1 j})}. \tag{25}$$

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

$$\tilde{\mathcal{S}}_{l|i_1}(\theta) = \int \frac{\exp\left(\hat{\rho}_l V_{i_1 l}(\theta) - c_l(\theta)\right)}{1 + \sum_{\ell \in \{l_r, l_e\}} \exp\left(\hat{\rho}_\ell V_{i_1 \ell}(\theta) - c_\ell(\theta)\right)} dF(i_1). \tag{26}$$

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

$$g_3(\theta) = E[\widehat{\mathcal{S}^o_{lmt|i_1}}] - \tilde{\mathcal{S}}_{l|i_1}(\theta), \tag{27}$$

where $E[\widehat{S^o_{lmt|i_1}}]$ 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. I use a weight matrix based on the inverse variance matrix of the data moments. For a given set of (θ_2, θ_3) I compute the predicted market shares $\tilde{s}_j$ for each vehicle product in the sample data period based on the equations in (14). 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

$$\boldsymbol{\delta}^{n+1} = \boldsymbol{\delta}^n + \ln(\hat{\mathbf{s}}^o) - \ln[\tilde{\mathbf{s}}(\boldsymbol{\delta}^n, \boldsymbol{\theta})], \tag{28}$$

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 I construct the GMM estimator relying on three sets of moments as follows.

The estimation process starts with an initial guess of $(\boldsymbol{\delta}^0, \theta_2^0, \theta_3^0)$, and a vector of simulated $\nu_{i_k}^{\mathrm{EV}}$. Then I iterate the mean valuations $\boldsymbol{\delta}$ through contraction mapping$\hat{\boldsymbol{\delta}} = \boldsymbol{\delta}(\hat{\theta}_2, \hat{\theta}_3)$ 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. I 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 $\boldsymbol{\delta}$. I use our first stage estimate $\hat{\delta}$ as an estimate for δ and employ an IV regression based on the equation

$$\hat{\delta}_j = \bar{\alpha} p_j + \bar{\kappa} I_{j \in \mathcal{J}_{\mathrm{EV}}} + x_j \beta + \eta_m + \eta_t + \xi_{\mathrm{make}} + e_j. \tag{29}$$

Market Size. Given that license plate application and vehicle purchase is available to all qualified households in a market, I 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.

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 I 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:

$$E[e_j(\theta_1)|\boldsymbol{Z}] = 0, \tag{30}$$

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

5.2 Parameter Estimates

Table 2 presents parameter estimates for our demand-side system. In the first panel, I 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

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

diffusions. In addition, I estimate a significantly large random coefficient for EVs which is around 3.849 representing substantial heterogeneity in tastes towards EV models across 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 $\times$ 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: *I 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, I 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, I 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. I 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, I 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. I 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, I 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, I 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, I 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 -5.2572 and -4.3403, 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

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

Group	Own-Price Elasticities	Cross-Price Elasticities	
		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. I 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.*

between EVs and GVs is about 0.0080. 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 quota or ban on gasoline vehicles (or a non-tradable GV quota) may lead to large deadweight loss. Furthermore, the average group-level cross-price elasticities between EV products are about 3.3555 indicating electric vehicles are close substitutes to each other in the sample period.

I 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.

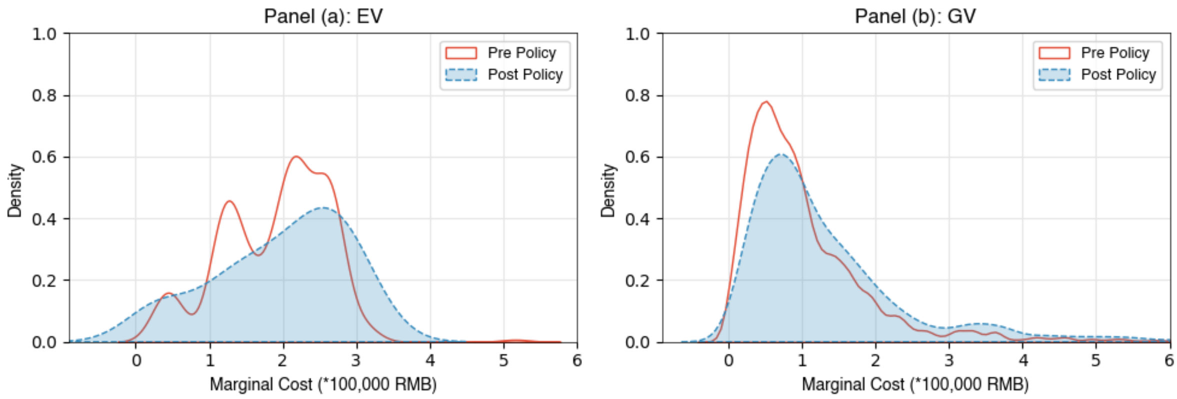
5.3 Model Fit

Table 7 in Appendix G presents the correlations between moments I 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.

5.4 Marginal Cost Estimates

Based on the demand estimates, I compute the marginal cost c_j of each vehicle model j using equation **??**. 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, I 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 use the model estimates and counterfactual simulations to evaluate how EV subsidy and the GLP policy affect consumer purchase decisions, producer pricing behavior, and welfare outcomes. The counterfactual analysis focuses on sample data from Beijing in 2015, a period when multiple EV producers were competing in the market and both policies were implemented.

For each vehicle product, I simulate market outcomes for the year 2015 that would have occurred in the vehicle markets under the following three scenarios where the local government implemented: (i) *No EV policies*, (ii) *only EV subsidies*, and (iii) *only the GLP policy*.

More specifically: (i) *No EV policies:* In this scenario, I assume both EV policies were removed by combining the settings in the previous two cases.

(ii) *only EV subsidies*: In this scenario, I assume the GLP policy was removed by setting that first-time buyers can only choose between regular license plate or no purchase in the choice for license plate application.

(iii) *only the GLP policy:* In this scenario, I assume that EV subsidies were removed by setting the subsidy amount in equation (5) to 0.

The techniques I use to perform the counterfactual analysis is illustrated in details in Appendix H. The setup of this counterfactual simulation allows us to decompose the impacts of EV subsidies and the GLP policy in the EV and GV market and discuss the interactions between the two policies.

In my main counterfactual results, I assume that changes in the policies lead to shifts in consumer purchase decisions and adjustments in producer pricing, while holding consumer taste parameters and producer marginal costs constant.

Section 6.1 discusses potential effects of the EV policies implied by the model. Section 6.2 presents consumer's responses to the changes of the EV policies in the EV and GV market. Section 6.3 explains firms pricing behaviors in response to the EV policies, and shows how the GLP policy affects the market power of EV producers. Section 6.4 evaluates the welfare impacts of both policies considering environmental externalities. Section 6.5 introduces additional EV policies with more flexibility, and discusses the policy implications.

6.1 Potential Effects of EV Subsidy and the GLP Policy

Before proceeding, it is instructive to highlight the potential effects of EV subsidy and the GLP policy implied by the model and I attempt to quantify.

Policy Impacts on Sales. The demand side of our structural model captures the direct impacts of EV subsidy through the prices perceived by consumers. A reduction in the amount of EV subsidy would affect consumers choices for EVs through the price impact. Also, the quota policies, including quota constraints and the GLP policy could affect the sales of EV through the quota impacts. The rationales behind the quota impacts is that the GLP policy implemented in Beijing, 2015 exempts EV consumers from the binding license quota system, offering them additional EV license quotas. The increased EV quotas could potentially allow more EV sold to first-time consumers who need license plates to register new vehicles given their preference heterogeneity.

The estimated model also recovers the underlying substitution patterns between EVs and GVs, capturing the substitution impacts on sales of EVs and GVs due to the EV policies. For example, EV subsidies could lead consumers to substitute GVs for EVs due to the price effect.

Policy Impacts on Pricing and Market Power. The model allows for auto manufacturers to adjust vehicle prices in response to the changes of EV policies. For example, an increase the amount of EV subsidies to consumers might also lead to higher EV prices, which pass the EV subsidies to the automakers through their pricing strategies. The GLP policy may grant EV manufacturers greater market power to set higher prices as it separate the EV market from the GV market.

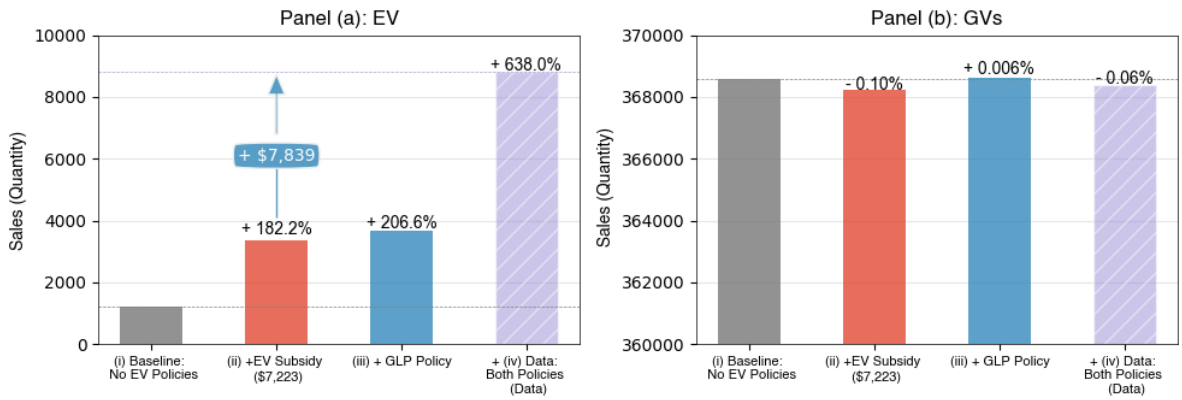
Policy Impacts on Welfare Outcomes. Vehicle usage is closely related to environmental externalities, including carbon emissions, air pollution, congestion, space, and crash costs. The adoption of EVs can bring environmental benefits by reducing carbon emissions and pollution (Holland et al., 2016; Mitropoulos, Prevedouros and Kopelias, 2017; Rapson and Muehlegger, 2024). My analysis quantifies the welfare outcomes of EV subsidies by examining changes in consumer surplus and producer profits due to subsidies, potential environmental gains from substituting GVs with EVs, and the welfare cost of government expenditure on subsidies.

For the GLP policy implemented during the sample period in Beijing, it provided consumers with additional EV quotas under the binding license quota system. I evaluate the welfare outcomes of the GLP policy by keeping the regular license quota number fixed and considering the changes in consumer surplus and producer profits due to additional EV quotas, potential environmental externalities from increased EV usage and the substitution between EVs and GVs. Note that the market distortions caused by the regular license quota systems are not considered part of the welfare outcomes of the GLP policy in the following analysis. I separately quantify the market distortions and welfare results caused by the regular license quota system in Appendix I.

6.2 Impacts on Sales

Figure 4 displays the total sales of EVs and GVs in the three counterfactual scenarios and the data case in Beijing, 2015. The percentage changes in Figure 4 represent the sales changes in the counterfactual scenario relative to the baseline scenario where neither EV subsidy nor the GLP policy was implemented.

Figure 4: Counterfactual Sales Impacts



***Notes**: The figure plots the sales of EVs and GVs in the three counterfactual simulations - (i) baseline scenario: No EV policies; (ii) only EV subsidy (amount of $7,223) (iii) only the GLP policy, and (iv) the data case (both policies) in the auto market of Beijing, 2015. The percentage change in each scenario w $(= ii, iii, iv)$ is defined as the ratio of (total sales in scenario w - total sales in the baseline scenario) to total sales in the baseline scenario.*

The counterfactual results in Panel (a) of Figure 4 show that if the government had not implemented the two primary demand-side EV policies (denoted as the baseline scenario), the total number of EVs sold in Beijing in 2015 would have been around 1,193, representing an 86.5% decrease compared to the EV sales observed in the data, holding all other conditions constant. Given the baseline scenario, if the government had only implemented the same amount of EV subsidies, the total sales of EVs in Beijing in 2015 would have increased from 1,193 to 3,367, approximately 182.2% higher. If the government had only implemented the GLP policy, the total number of EVs sold in Beijing would have been

3,658, approximately 206.6% higher than the baseline scenario. These results suggest that both subsidies and the green license policy have a significantly large impact on promoting EV sales, implying substantial efficacy of EV subsidies and the GLP policy in the adoption of EVs.

Moreover, the total EV sales increase in the data case where both policies were implemented is higher than the sum of sales increase in the counterfactual scenario (ii) and scenario (iii), suggesting that a combination of EV subsidy and the GLP 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 the two demand-side policies complement each other in promoting EVs.

Impacts on GV Substitution. Despite the sizable impacts of promoting EVs, I find that EV subsidies and the GLP policy in our context have little impact on the GV market. Scenario (ii) in Panel (b) of Figure 4 shows that the total sales of GVs would have decreased by only 0.10% relative to the baseline scenario (i), amounting to 385 fewer GVs, had the government introduced EV subsidies. The small decrease in GV sales compared to the substantial increase in EV sales in Scenario (ii) with EV subsidies indicates that the subsidy policy primarily incentivized the adoption of EVs by attracting potential consumers who were previously outside the vehicle market and had not intended to purchase cars. This outcome deviates from the policy's intended goal of encouraging substitution from GVs to EVs.

Regarding the GLP policy, the total sales of GVs would have increased by 0.006%, amounting to 22 more GVs, had the government only implemented the GLP policy, as illustrated in Scenario (iii) of Panel (b) in Figure 4. While the increase in total GV sales may seem counterintuitive, it is reasonable because EV prices would have been significantly higher relative to the baseline scenario had the government implemented the GLP policy. As a result, some consumers who would have chosen EVs might opt for GVs due to the price effects.

Overall, the resulting changes in the counterfactual scenarios suggest a weak substitution pattern between EVs and GVs due to the subsidy and the GLP policy in the context of Beijing, 2015. This finding is consistent with our previous estimation results in Section 5, which show that the group-level cross price elasticities between EVs and GVs are relatively small compared to the within-group cross price elasticities.

How much subsidy is the GLP policy equivalent to? My findings have shown the comparable and sizable impacts of both EV policies in promoting EVs. Given the minimal cost of implementing the GLP policy[1], it's natural to ask: how much money does the GLP policy save the government in deploying EVs? To answer the question and provide a comparison between the two policies, I simulate the additional amount of subsidies per EV that would be necessary to replace the GLP policy and maintain the number of EVs deployed at the observed level (8,804 EVs) based on the counterfactual scenario (ii) in the sample data from Beijing, 2015.

The results show that the government would have needed to offer each EV buyer an additional subsidy of 48,837 RMB (approximately \$7,839) to replace the GLP policy and maintain the number of EVs deployed at the observed level (8,804 EVs) in Beijing in 2015.

In total, the Beijing local government spent \$63.59 million on EV subsidy programs in 2015. The implementation of the GLP policy had saved the government \$69.01 million (\$7,839 $\times$ 8,804) in deploying EVs, which accounts for 27.60% of the government budget for EV subsidy programs. These results imply the cost-effectiveness of the GLP policy compared to subsidies.

So far, my analysis has demonstrated how the policies affect consumer purchase behaviors of EVs and GVs, addressing the following policy questions: How many EVs does each policy deploy on the road? How many GVs were substituted by EVs under the EV policies? How much subsidy is the GLP policy equivalent to? Next, I will present how auto manufacturers adjust their pricing strategies in response to the EV policies.

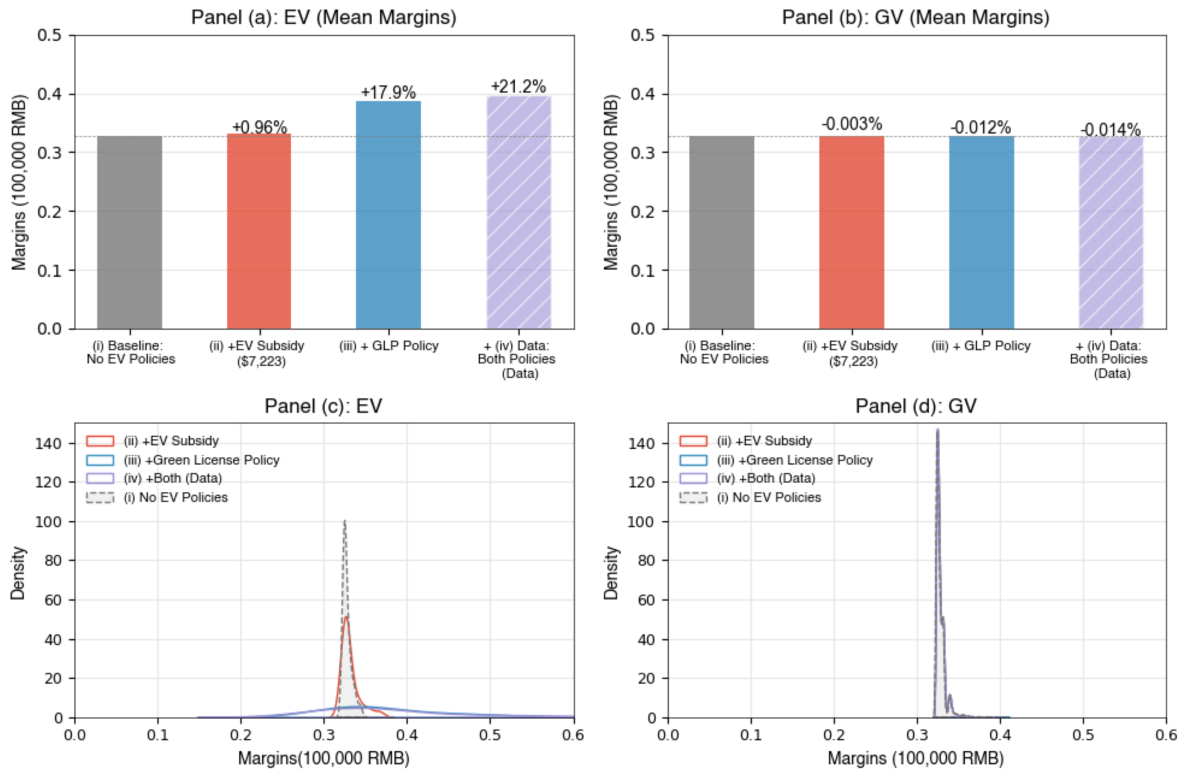
6.3 Impacts on Prices and Market Power

Figure 5 presents the average (unweighted) and the distributions of EVs margins and GVs margins simulated in the three counterfactual scenarios and the data case based on the auto market of Beijing, 2015. Here, the margin ($p - mc$) is defined by vehicle price minus marginal cost. It measures the adjustment in auto manufacturers' pricing strategies

[1]The cost of implementing the GLP policy is considered to be the cost of distributing a distinctive license plate for EVs.

because the marginal costs remain unchanged in the counterfactual simulations[1].

Figure 5: Counterfactual Margins Impacts



***Notes**: The figure plots the average (unweighted) and distribution of equilibrium EV and GV margins from three counterfactual scenarios: (i) baseline: no EV policies, (ii) only EV subsidies; (iii) only the GLP policy and (iv) the data case in the auto market of Beijing, 2015. Panel (a) and (b) display the average margins of EVs and GVs, where the percentage number represents the percentage differences in margins of the given counterfactual scenario relative to the baseline scenario (i). Panel (c) and (d) plot the distribution of equilibrium margins with the kernel density estimate in the EV and GV market, respectively.*

Panel (a) of Figure 5 shows that the average EV margins would have been around $5,262.3 had neither EV policy been implemented during the sample period. In this context, the average EV margins would have increased slightly by 0.96% ($50.5) if the government had only introduced the EV subsidy program providing $7,223 to each eligible EV. If the government had only implemented the GLP policy, the average EV margins would have increased by 17.9%, amounting to $941.6, in Beijing in 2015.

The distribution in Panel (c) of Figure 5 shows that the margins of EVs exhibit larger

[1]Appendix J displays the results of counterfactual prices.

variations in the counterfactual scenarios (iii) and (iv) where the GLP policy is in effect compared with the scenarios (i)(ii), implying EV manufacturers have larger pricing power among with the implementation of the green license policy.

The price impacts of the GLP policy are novel but not surprising because the GLP policy separates the EV market from the GV market, thereby protecting EV manufacturers from competition with GV manufacturers to some extent. This finding has an important implication: despite its cost-effectiveness, the GLP policy could distort the market by granting EV manufacturers greater pricing power over EV products.

Panel (b) and Panel (d) of Figure 5 show that the EV policies had little impact on the margins of GV producers, implying that these EV policies did not lead to significant changes in GV manufacturers' pricing strategies, holding all the other variables constant.

As displayed in Panel (d) of Figure 5, GV manufacturers did not respond much to the EV policies in prices which is consistent with our estimation results that substitutability between EVs and GVs is relatively low in the sample data period.

The GLP policy and EV market structures. To better understand how the GLP affects EV producers' market power under different market structures, I compare the markup changes in a market with multiple EV producers[1] (Beijing, 2015) to those in a market with a single EV producer[2] (Beijing, 2014). For comparison, I calculate the Lerner indices (defined as $\frac{p_j - mc_j}{p_j}$) to measure the product-level markup changes in the counterfactual scenarios, where p_j is the equilibrium price for vehicle j in the counterfactual simulation and mc_j is the estimated marginal cost for model j from the supply side.

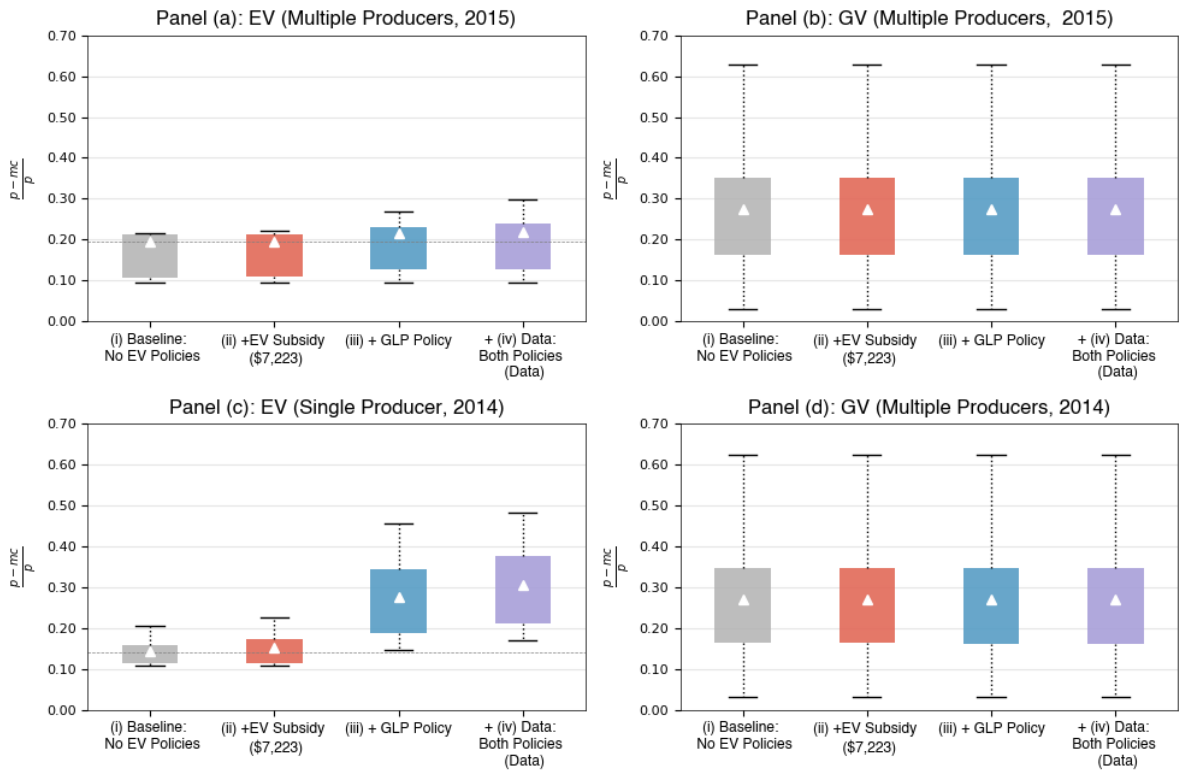
Figure 6 plots the markup distributions (mean, median, interquartile range, minimum, and maximum) of EVs and GVs. Panel (a) shows the counterfactual EV markups in a market with multiple (seven) EV manufacturers competing in EV prices. The average (unweighted) markup of EVs would have been 0.1944 if the government had implemented neither of the EV policies. If the government had only implemented the subsidy program, the average markup would have been 0.1957, which is 0.65% higher than the baseline sce-

[1]There were seven EV manufacturers producing eight products in the local market of Beijing, 2015.

[2]There was a single EV manufacturer (Beijing Automotive Group Co.) producing two products in the local market of Beijing, 2014.

nario. If the government had only adopted the GLP policy, the average markup would have increased to 0.2146, which is 10.38% more than the baseline scenario. The average markup with both policies in place was around 0.2190, which is 12.61% higher than the baseline scenario. The results in EV markup are consistent with my previous finding that the implementation of the GLP policy led to larger market power of EV producers in a market with seven EV manufacturers.

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 simulation scenarios where (i) no EV policies; (ii) only the EV subsidies; (iii) only the GLP policy and the data case (iv) both EV policies. I perform the counterfactual simulations using two samples from the data- Beijing, 2014 and Beijing,2015. Panel (a) and Panel (b) display the markup distributions of EVs and GVs under the data and three counterfactual scenarios in Beijing, 2015 where there were multiple (seven) producers competing in the EV market. Panel (c) and Panel (d) show the markup distributions of EVs and GVs under counterfactual simulations in Beijing, 2014 where there was a single producer (Beijing Automotive Group Co.) in the EV market.*

Panel (c) in Figure 6 shows the average counterfactual markup of EVs in a market with a single EV manufacturer producing EV products (Beijing, 2014). In the context of Beijing, 2014, the average (unweighted) markup was around 0.3052 in the data case, which is relatively high in the auto market (Berry et al. 1995). Had the government only implemented the GLP policy, the average markup would have been 0.2769, which reduced by 9.26% relative to the data case. Had the government only implemented the subsidy program, the average markup would have been 0.1519 with a reduction of 50.22% compared with the data case. The average markup of EVs would have been 0.1428, which is 53.24% if the government had implemented neither of the EV policies. The results demonstrate my previous findings, and suggest that market structures matter in the policy evaluations of the EV policies. In a market with a single EV manufacturer producing EVs, the GLP policy led to very high market power of EV producers and thus harm the consumers with high EV prices.

Panel (b) and (d) in Figure 6 show that the average markup of GVs were around 0.2750 in Beijing, 2015, and 0.2707 in Beijing, 2014. The markup did not change significantly over the counterfactual simulations or over time. The magnitude of product-level markup is comparable with recent literature in the vehicle market (Grieco et al., 2023).

The GLP policy and the subsidy pass-through. To elucidate how the GLP policy shapes the impacts of EV subsidies on producers' pricing strategies, I examine the subsidy pass-through rate to EV producers in the context with and without the GLP policy. The subsidy pass-through is a measure commonly used in public economics to reflect the subsidy distribution among consumers and producers (Kelly 2014; Pless and Van Benthem 2019). In this paper, I define the subsidy pass-through as the rate of subsidy pass-through to producers. It is written as $\frac{p^w - p^0}{d_w}$, where p^w is the equilibrium vehicle prices in the counterfactual scenario w with subsidies where $w = (ii), (iv)$. p^0 is the competitive market equilibrium prices simulated in the baseline counterfactual scenario (i) without subsidies; d_w denotes the amount of subsidy in the counterfactual scenario w. d_w is a constant equaling to $7,223 for this analysis. The rate of subsidy pass-through to producers in my setting falls between 0 and 100 percent with higher values (or lower values) indicating more subsidies benefit producers (or consumers). The graph interpretation of the subsidy pass-through is in Appendix H.1.

The calculation results show that the average pass-through rate to producers would have been approximately 1.35% in the counterfactual scenario (ii) where only EV subsidies had been implemented. In the data case where both EV subsidies and the GLP policy were in place, the rate of subsidy pass-through to producers stands at 25.72% implying 25.72% of EV subsidies are transferred to producers in place of the GLP policy. Especially, 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.

These findings on price impacts have important implications for policies aimed to deploy the electric vehicles (EVs). First, I 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.

6.4 Welfare Outcomes

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,

$$\overline{CV^w} = \int_i \frac{1}{\bar{\alpha}} \left[\ln\Big(\sum_{j \in \{0, \mathcal{J}^w\}} \exp(\delta_j^w + \mu_{ij}^w) \Big) - \gamma_i \Big) \right] dF(i), \tag{31}$$

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

$$\Delta \overline{CS^w} = M_w \overline{CV^w} - M_0 \overline{CV^0}. \tag{32}$$

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

$$\Delta \overline{PS} = \sum_j \left[(p_j^{w*} - mc_j) q_j^{w*} \right] - \sum_j \left[(p_j^{0*} - mc_j) q_j^{0*} \right], \tag{33}$$

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 the welfare analysis, I focus on the potential positive externalities, such as environmental gains due to the substitution effect in the former case. I 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). I take the estimate as the average VMT for both EVs and GVs in Beijing, 2015. By multiplying the factors above, I calculate the annual external cost due to the usage of the vehicle in group $g(g \in \{EV, GV\})$ as

$$AEC_g = MEC_g * VMT * Q_g. \tag{34}$$

To quantify the total externalities associated with the usage of EVs and GVs, I need to make assumption about the time horizon over which the external costs accrue. Though the license plate could last multiple vehicle usage, I 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

$$TEC = \sum_{g \in \{EV, GV\}} AEC_g * LS_g. \tag{35}$$

Net Welfare Surplus. Given the assumption of minimum vehicle lifetime (6 years), I compute the net welfare surplus in the vehicle market by summing up the total consumer surplus, producer profits, government expenditure and externalities.

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, I 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

Table 4: Welfare Comparison

Scenarios	Null	(I)	(II)	(III)
Beijing, 2015	No EV Policies	+ EV Subsidy	+ GLP Policy	+ Both (Data)
Regular License Quotas	105,600	105,600	105,600	105,600
EV License Quotas			20,000	20,000
EV Sales	1,193	3367	3658	8804
Welfare (in dollar millions)		Δ Relative to the Null Scenario		
Consumer Surplus (CS)	6356.97	37.40	41.58	130.22
Producer Surplus (PS)	1965.24	10.22	20.14	62.02
EV Producer	6.93	12.53	20.08	63.53
GV Producer	1958.31	-2.31	0.06	-1.51
Government Expenditure (GExp)	0.00	24.32	0.00	63.59
CS+PS-GExp	8322.21	23.30	61.71	128.65
Externalities Cost (EC)	-7523.92	1.96	-7.13	-15.97
Net Welfare Surplus	798.29	25.26	54.58	112.68

***Notes**: The table displays the welfare consequences of applying the EV subsidy, the GLP policy and both in the automobile market, measured in a million of dollars in the sample data period (Beijing, 2015). The externalities cost provides the average estimated externalities due to the usage of EVs and GVs based on assumptions of average external cost with minimum vehicle lifetime (7 years).*

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.

6.5 Additional EV Policies With More Flexibility

In addition to these simple policies, I also consider two additional policies with more flexibility based on current demand-side EV subsidies and the GLP policy.

6.5.1 Reserving EV Quots

Optimal Subsidy

The optimal policies depend on my model calibration, and the sensitivity of my calculations to a key parameter, the SCC, The trade-off of subsidy policy is between the increase in the consumer surplus, producer surplus as well as the potential environmental gains due to substitution from GVs to EVs and the funding cost of government expenditure. Because I do not observe any government's funding costs directly, however, designing policymaker's optimal subsidy under the green license policy is a task outside the scope of the current analysis.

7 Conclusion

Over the last decade, electric vehicles have attracted increasing attention from policymakers due to their potential to transform transportation. Meanwhile, a variety of EV policies to support EV adoption have been instituted in key markets, stimulating a major expansion of EV markets. Employing a structural model for vehicle demand and supply and using numerical simulations calibrated to the auto market in Beijing, I analyze two primary demand-side policies—EV subsidies and the green license plate policy—evaluate their welfare outcomes, and compare them with other policy options.

Table 5: Welfare Comparison with Flexible Policies

Scenarios	Null	(I)	(II)	(III)
Beijing, 2015	No EV Policies	+ EV Subsidy	+ Adjusted GLP Policy	+ Both (Data)
Regular License Quotas	125,600	125,600	105,600	105,600
EV License Quotas			20,000	20,000
EV Sales	959	3,472	3658	8804
$ in million			Δ Relative to Baseline	
Consumer Surplus (CS)	6712.08	42.40	-313.54	-224.89
Producer Surplus (PS)	2084.35	11.35	-98.97	-57.09
EV Producer	5.16	14.42	21.36	65.30
GV Producer	2079.19	-3.08	-120.33	-122.38
Government Expenditure (GExp)		25.08	0.00	63.59
CS+PS-GExp	8796.43	28.66	-412.51	-345.57
Externalities Cost (EC)	-7959.95	3.57	428.90	420.06
Net Welfare Surplus	836.48	32.24	16.39	74.49

Notes*: The table displays the welfare comparison of applying the EV subsidy, an adjusted GLP policy and both under an adjusted quota policy in the automobile market, measured in a million of dollars in the sample data period (Beijing, 2015). In the welfare results, I keep the total quota numbers (sum of regular license quotas and EV license quotas) as fixed and assume the adjusted GLP policy reserved EV quotas for EV buyers.*

My study provides an empirical analysis on how and to what extent the government can promote the adoption for electric vehicles through subsidies and the GLP policy and evaluates the welfare outcomes of these policies addressing environmental concerns associated with vehicle usage.

Moreover, my model estimation finds that the substitutability between EVs and GVs was low during the sample data period. As a result, my counterfactual analysis shows that both EV subsidies and the GLP policy had limited impacts in encouraging consumers to substitute GVs with EVs in Beijing, contrary to the primary rationale of these policies. My analysis also demonstrates that, despite its minimal cost, the green license plate policy could lead to high market power for EV producers due to the policy segmenting the vehicle market. This finding highlights the importance of accounting for market structure in policy evaluations in the auto market.

Most importantly, for policymakers concerned with EV adoption policies, there are several aspects of this analysis that can be extended. First, although quotas in the auto market may seem extreme and have not yet been part of the policy discussion surrounding electric vehicles, my results suggest that implementing the green license plate policy together with a vehicle quota system could lead to net welfare gains under certain conditions. This is particularly relevant for economies with significant environmental externalities caused by vehicle usage or those with tight budgets and high funding costs for EV subsidy programs. Second, in economies where restrictive license quota systems have been adopted, a policy that merely provides distinctive license plates to EV buyers may seem costless. However, it could lead to unexpectedly high market power for EV producers, resulting in market distortions given the competitive conditions.

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.

de Chaisemartin, Clément and Xavier D'Haultfœuille (2020) "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, 110 (9), 2964–2996, 10.1257/aer.20181169.

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.

Rapson, David S and Erich Muehlegger (2024) "The Economics of Electric Vehicles," *Working Paper*.

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

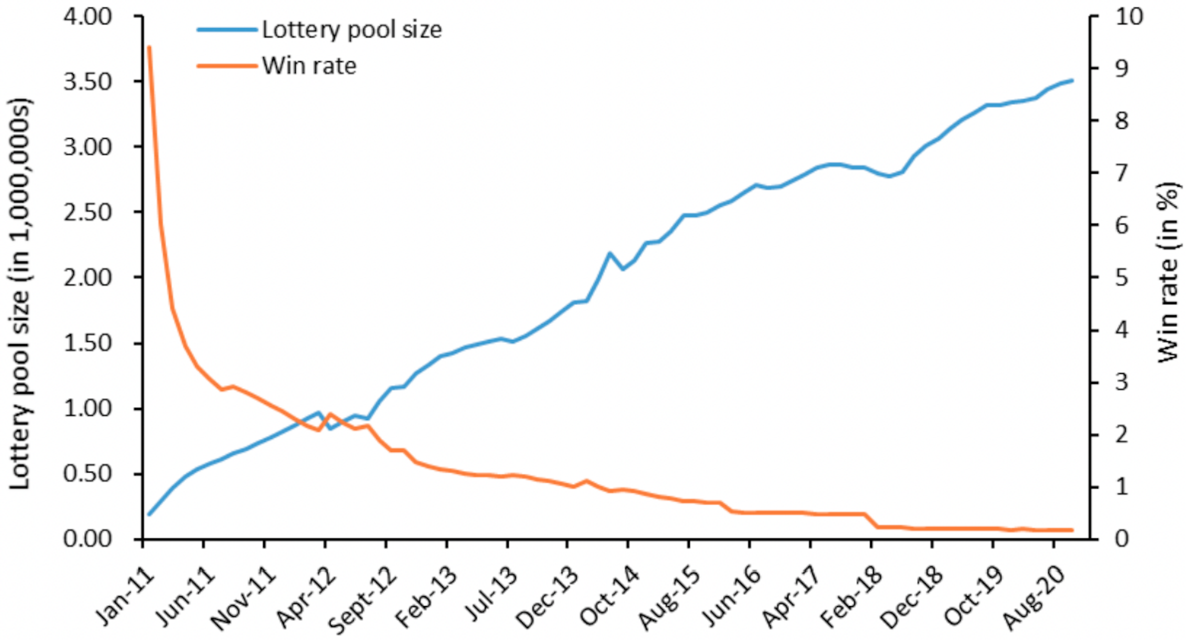
B.1 Beijing

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 7 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.

Figure 7: 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).

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

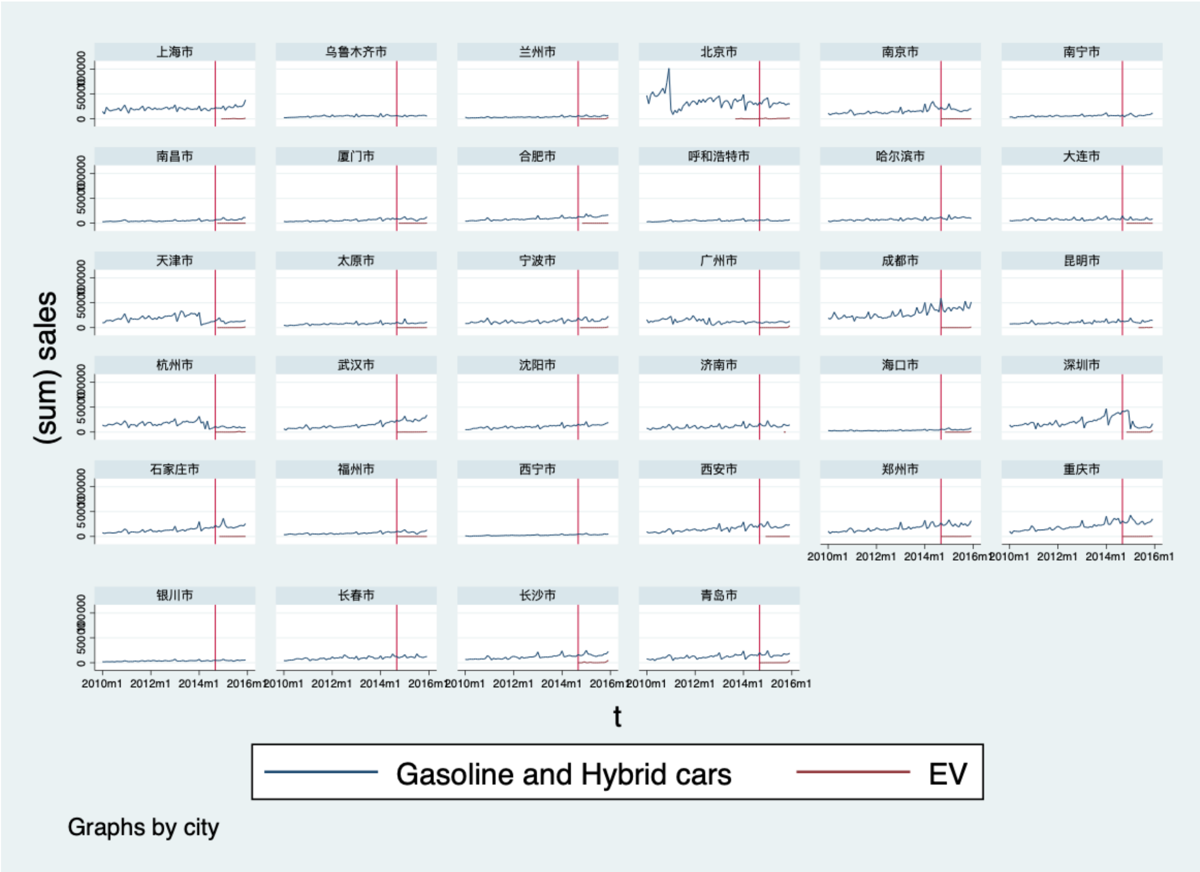
To understand how the quota policies affect the sales of conventional cars and EVs in Beijing, I first check quantify sales changes of gasoline cars before and after the policy implementation. As shown in Figure 8, total number of gasoline car sales decrease sharply following the policy implementation in Beijing and Tianjin offering an indication that the policy did restrict consumers' choices of buying cars. By comparing with Tianjin and Shanghai, I 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 8: 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 9 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 9: 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.

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

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. I take the average of outside shares data among regular license winners from the bi-monthly data in Beijing as Moment 2. I take the average outside shares data among regular license winners from the bi-monthly data in Beijing as Moment 2.*

H Empirical Methods for Counterfactual Analysis

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

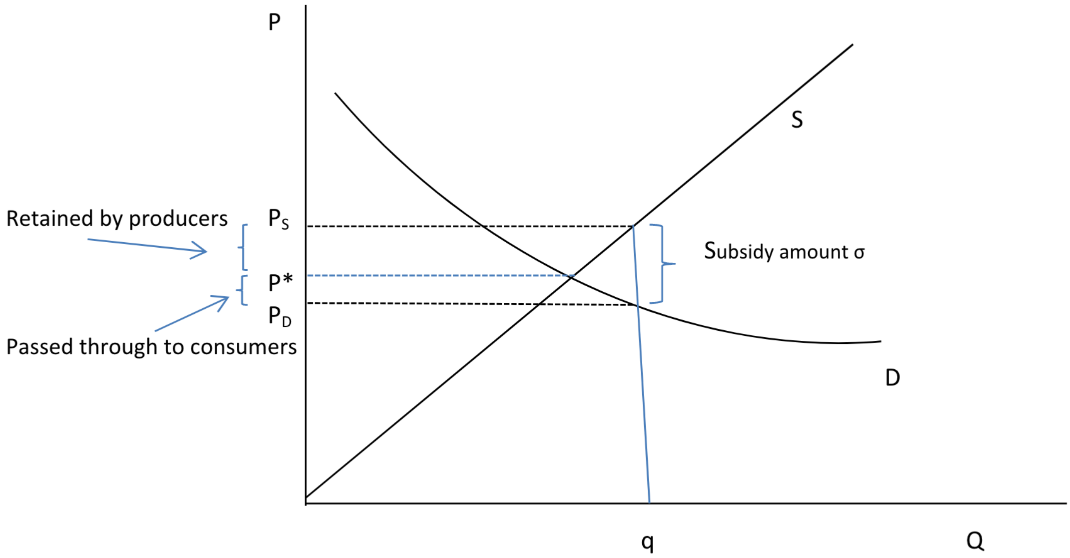
To start with, I make the following assumptions in the counterfactual analysis. First, I assume the consumers' taste parameters, marginal costs of production, and product offerings fixed under different counterfactual scenarios. A possible concern about this assumption is that both subsidy and the green 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.

In the counterfactual analysis, I study the impacts of removing the EV policies on the market outcomes of EVs and GVs considering firms' pricing in response to the policy changes. In the counterfactual scenario (i), only EV subsidies were in effect. I remove the EV subsidies but remove the GLP policy 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 (2), only the GLP policy was in effect. I remove the subsidy policy by setting the subsidy amount in equation (5) to 0. In the counterfactual scenario (3), I remove both EV subsidy and the GLP policy by combining the settings in the previous two cases.

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

H.1 Subsidy Pass-Through

Figure 10: Subsidies in Competitive Markets



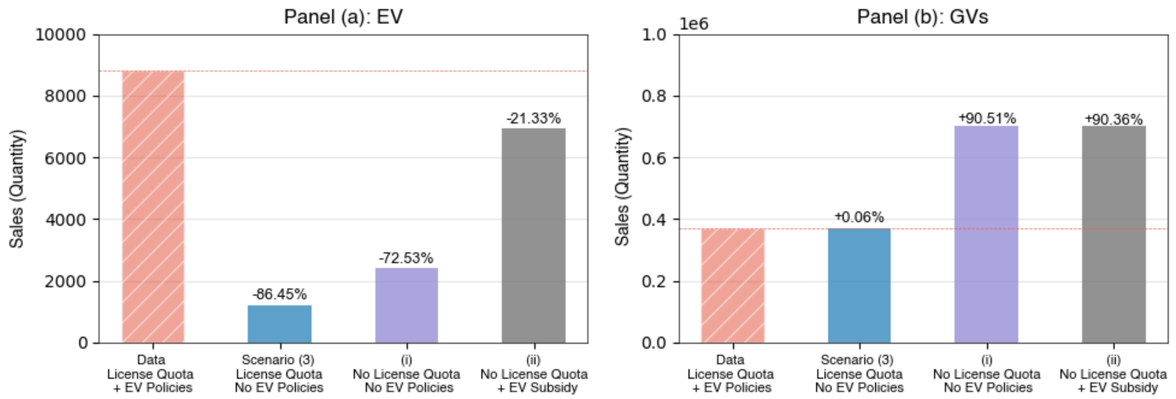
I Empirical Analysis of the License Quota Policy

To illustrate the overall impacts of the license quota policy together with the EV promotion policies, I present the sales impacts of the license quota policy and report the welfare results including the impacts of quota constraints in the context of Beijing, 2015. Different from earlier studies on the vehicle license allocation system (Li, 2018; Xiao, Zhou and Hu, 2017,Guo and Xiao, 2022), my analysis focus on the interaction between EV promotion policies and the license quota policy.

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.

Table 11 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 11: Counterfactual Sales



***Notes**: The figure illustrates the counterfactual sales of EVs and GVs across three simulation scenarios for Beijing in 2015. In Scenario (3), I retain the license quota policy but eliminate both EV policies (subsidies and the green license policy). In Scenario (i), I remove the license quota policy along with both EV policies. In Scenario (ii), I 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.*

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 (31). 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 I (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, I approximate the total changes in consumer surplus by

$$\Delta CS = -M \times \overline{CV^w}, \tag{37}$$

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

$$\Delta PS = \sum_j \Big[(p_j^{w*} - mc_j)q_j^{w*} - (p_j^{0*} - mc_j)q_j^{0*}\Big], \tag{38}$$

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, I 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), I 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 8 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, I 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.

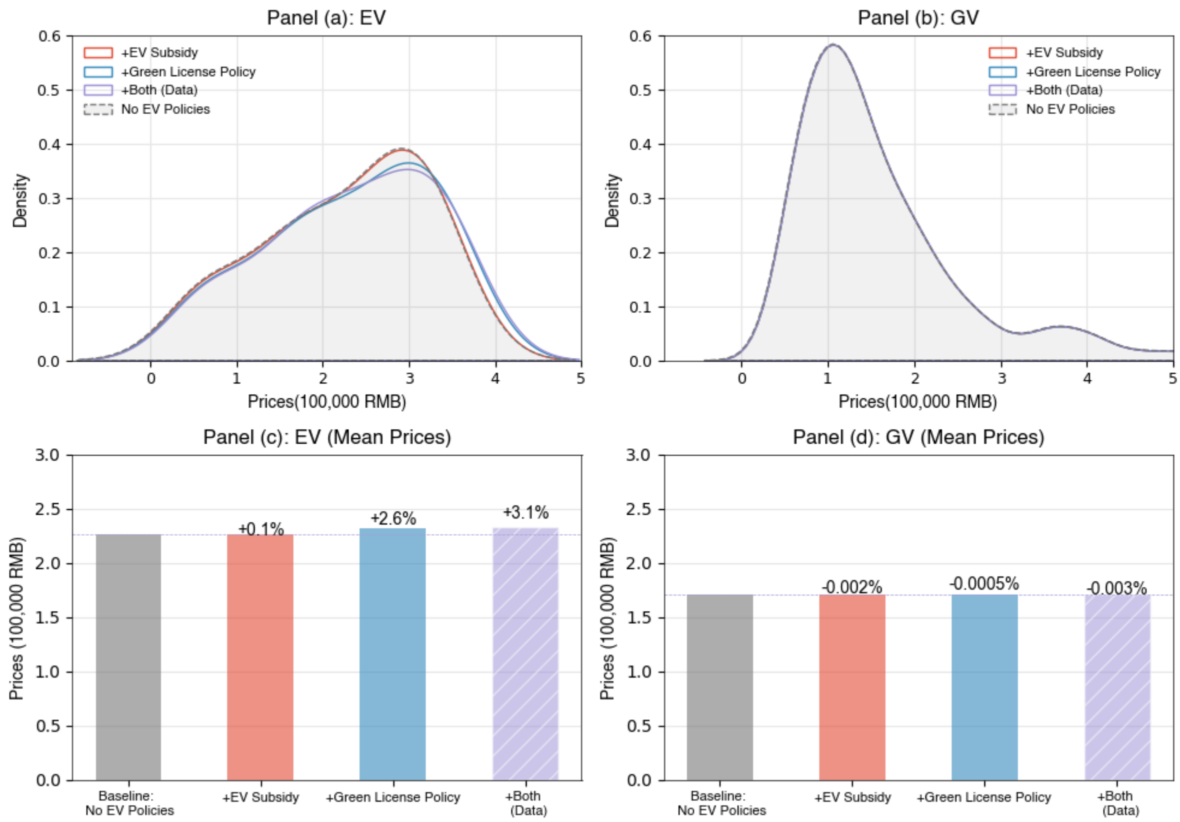
Table 8: Welfare Results

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.*

J Impacts of EV Subsidy and the GLP Policy on Prices

Figure 12: Counterfactual Prices Impacts



***Notes**: The figure plots the average and the distribution of equilibrium margins of EVs and GVs in the simulated auto market of Beijing, 2015. The simulation results come from three counterfactual scenarios: (i) baseline: no EV policies, (ii) only EV subsidies; (iii) only the GLP policy and (iv) the data case. Panel (a) and (b) display the average margins of EVs and GVs in the four scenarios. Panel (c) and (d) present margins distribution with the kernel density estimate plot in the EV and GV market, respectively. The percentage changes represent the percentage of the margins changes relative to the basline scenario.*

K Whitelist

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 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, I exclude subsidies in this counterfactual analysis. In this case, I assume the previously discussed counterfactual scenario (1) where I 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.

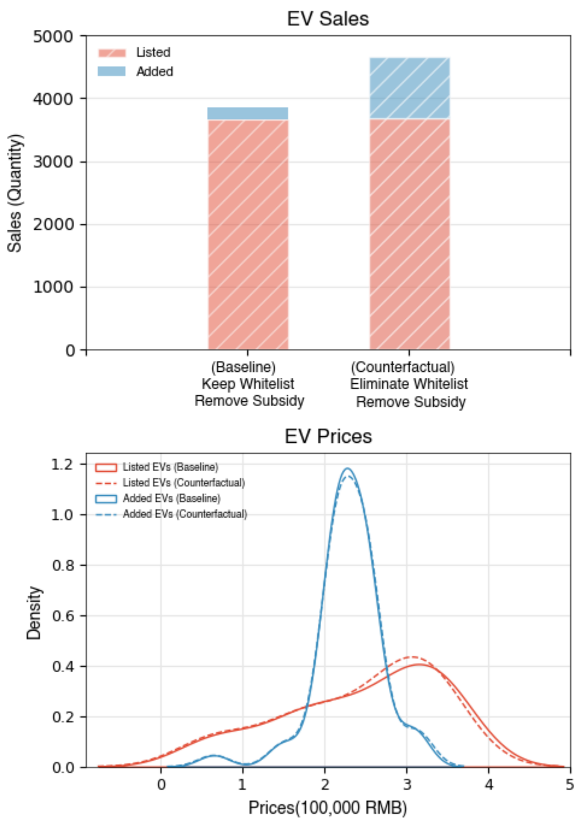
Figure 13 presents the equilibrium sales and prices of EVs in the baseline and counterfactual scenario. The equilibrium impacts on GVs are not displayed as the impacts are minimal. The results suggest that 1) eliminating the whitelist could lead to a significant increase in the sales of EVs originally 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

[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.

the whitelist in the green license policy does not affect the equilibrium sales and prices of gasoline vehicles. I 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 I simply eliminate the whitelist in the green license policy.

Figure 13: 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 I 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*