Demand-side Policies for Electric Vehicle Adoption: Evidence from Beijing

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Abstract

In response to global climate change and environmental problems, policymakers around the world have implemented various initiatives to promote electric vehicle (EV) adoption. I employ a structural model to evaluate the impacts of two demand-side interventions: EV subsidies and the green license plate (GLP) policy on EV adoption and examines the welfare impacts of these two policies. Using data from China's automobile industry, I estimate a demand model for vehicles that endogenizes consumer choices for license plates while accounting for consumer demographic heterogeneity. On the supply side, I estimate marginal costs based on Nash-Bertrand pricing. My counterfactual analysis indicates that the GLP policy was remarkably effective in boosting EV sales, equivalent to approximately $7,839 per EV in subsidies in Beijing, 2015. However, while it was effective in increasing sales, the policy also led to greater market power for EV producers, resulting in higher EV prices. When considering environmental externalities, both the EV subsidies and the GLP policy enhance net welfare surplus by 3.16% and 6.84%, respectively. Furthermore, I analyze the optimal level of EV subsidies in conjunction with the GLP policy and propose alternative policy designs that could be more efficient than the current practices in Beijing.

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1 Introduction

Regulators view electric vehicles (EVs) as a promising solution to the environmental and energy challenges in the automobile industry (Holland, Mansur, Muller and Yates, 2016). As a result, policymakers worldwide have implemented various measures to encourage the adoption of electric vehicles as part of the emerging green industries.

In China, the local government in Beijing has introduced two primary demand-side policies to promote the adoption of electric vehicles (EVs) since 2014. These policies include a financial incentive, a demand-side subsidy for EVs, and a non-financial incentive, the green license plate policy. The green license plate policy (referred to as the GLP policy) provides EV buyers with distinctive license plates and grants them a registration privilege in Beijing, where non-electric vehicle purchases are subject a stringent vehicle license quota system. The primary justifications for these two policies is to encourage the substitution of gasoline vehicles (GVs) with EVs and reduce 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 result in net welfare gains, considering the expected environmental externalities. Specifically, I ask the following questions: How many EVs does each policy deploy on the road? How many GVs have been replaced by EVs due to these two policies? How do producers respond to the EV policies in terms of pricing behavior? What are the welfare implications of these policies, accounting for market distortions and environmental externalities?

To answer these questions, I employ a structural model in which the demand side is a discrete choice model which extends the framework of Berry, Levinsohn and Pakes (1995) and integrates the subsidy factors into vehicle choices. Specifically, I develop a demand model which endogenizes consumers' choices for license plate types into consumers' vehicle purchase decisions allowing for consumer demographic heterogeneity. On the supply side, I assume automobile producers engage in a Nash-Bertrand pricing game.

My model addresses two identification issues in the demand estimation for EVs. First, the observed sales of EVs depend not only on consumer preferences for vehicles products but also on the choice set constraints imposed by the policy (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022). The green license plate policy, which exempts EV consumers from a restrictive license quota, requires those choosing EV license plates to select their most preferred option from a limited choice set of eligible EV products, rather than from all available options (Berry, Levinsohn and Pakes, 1995). To recover consumer preferences for electric vehicles from observed product shares, I model consumers' preferences for license plate types and take their endogenous license choices into account in the demand estimation for vehicle products.

The second identification issue is that, as econometricians, we cannot directly observe consumers' heterogeneous preferences for EVs from aggregate data. However, it is crucial to account for this consumer preference heterogeneity when analyzing endogenous license plate choices or evaluating the impacts of EV policies. For example, consumers with a strong preference for EVs are more likely to apply for EV license plates. Also, buyers who value EVs would have likely purchased them even in the absence of EV promotion policies (Xing, Leard and Li, 2021). To address this issue, I incorporate a random taste parameter in the discrete choice model to account for consumer taste heterogeneity. I then identify this taste heterogeneity through microdata, following the approach outlined by Berry, Levinsohn and Pakes (2004a) and Grieco, Murry and Yurukoglu (2023).

With the structural model, I estimate the demand for EVs and gasoline vehicles (GVs), and recover the distribution of consumer heterogeneity taste for EVs leveraging 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 indicate that, on average, consumers have a strong negative preference for electric vehicles (EVs). However, there is substantial variation in the preferences, suggesting that consumer attitudes toward EV products are highly heterogeneous. To analyze the substitution patterns between EVs and GVs, I examine the price elasticities derived from the model estimates. The results show that the average cross-price elasticity within the EV product group is around 3.3555, indicating a strong tendency for consumers to substitute between different EV products. In contrast, the cross-price elasticity between EVs and GVs is 0.0080, suggesting limited substitution between these two vehicle categories during the sample period.

To validate the policy effects from the data, I measure the effects of 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 reduced-form findings demonstrate the effects of these demand-side EV policies. However, a structural model is needed to conduct the counterfactual analysis and analyze the interactions between the two policies.

Using the estimated structural model, I infer the marginal costs at the product level, assuming that auto manufacturers engage in a Nash-Bertrand game. I then conduct counterfactual simulations to investigate the impacts of two demand-side EV policies. In the counterfactual settings, I remove subsidies and the GLP policy separately for the sample period 2014-2015 in Beijing, while assuming that consumer preference parameters and product marginal costs remain the same.

Counterfactual analysis shows that if the government had not implemented EV subsidies nor the GLP policy, there would have been only 1,193 EVs sold, with the EV relative share of 0.32%, during the sample period (2015) in Beijing under vehicle quota constraints. In this context, introducing a subsidy program of $7,223 per EV would lead to 2,174 additional EVs, while the implementation of the GLP policy, which merely provides EV buyers with distinctive license plate quotas, would lead to 2,465 more EVs sold. The magnitude of these policy impacts is consistent with my previous findings in the reduced-form analysis. Together, the combination of EV subsidies and the GLP policy would deploy 7,611 more EVs on the road, raising the EV relative share to 2.33% in Beijing in 2015, suggesting complementary and sizable impacts of these two demand-side policies in promoting EVs.

By studying manufacturers' pricing responses to the counterfactual policy settings, I find that the GLP policy led to an increase of $941.6 (17.9%) in the average margins of EV producers and an increase of 10.38% in the average markups of EV producers during the sample period when there were seven EV manufacturers competing in the market. The sizable impact on EV producers' market power could be driven by the fact that the GLP policy separates the GV and EV markets and shields EV producers from GV competitors.

To better understand the welfare implications of the two EV policies, I conduct a welfare impact analysis that accounts for consumer surplus, producer surplus, government expenditure, as well as environmental externalities resulting from vehicle usage, such as carbon emissions and pollution. The findings reveal that the EV subsidy and the GLP policy would increase net welfare surplus by 3.16% (approximately $25.26 million) and 6.84% (approximately $54.58 million), respectively.

Furthermore, I propose an alternative GLP policy based on the current practices in Beijing, which addresses the policy rationale of encouraging EV-GV substitution by reserving EV quotas within the vehicle quota system. The welfare analysis indicates that, under certain assumptions regarding the environmental externalities estimates, this alternative GLP policy could lead to a net welfare increase of 1.96%. This improvement stems from a significant reduction in environmental externalities caused by GV usage, despite the market distortions introduced by quota constraints.

My paper contributes to recent studies that use demand estimation in the electric vehicle markets to evaluate EV related 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 (the GLP 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 EV-GV substitution 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). My study highlights the critical role of EV-GV substitution patterns in designing EV policies and measuring the environmental benefits of such policies.

My model builds on a specific setting related to earlier literature on the latent choice constraints of a discrete choice model (Abaluck and Adams-Prassl, 2021; Agarwal and Somaini, 2022), and my empirical method is based on the estimation and identification framework of previous work (Berry, Levinsohn and Pakes, 1995; Petrin, 2002; Berry, Levinsohn and Pakes, 2004a). As detailed above, I develop a two-stage discrete choice model that incorporates consumer endogenous choices for license types into vehicle purchase decisions to relax 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 which allow for counterfactual analysis and policy evaluations.

The remainder of the paper is organized as follows. Section 2 describes the empirical background including policies and data. Section 3 provides the reduced-form evidence on the effects of the GLP policy and local subsidies in Beijing. Section 4 describes the structural model. Section 5 discusses model estimation and the results. Section 6 presents 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.

In analysis for this paper, I compiled a dataset covering the years 2010 through 2015 in 34 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

Electric vehicles (EVs) have received significant global attention since the launch of the first EV model in 2010. Many policymakers regard them as a promising solution to environmental challenges, such as carbon emissions and air pollution caused by traditional gasoline vehicles (GVs), which have been major concerns over the past decade.

In China, the central government set a goal in 2010 to promote the adoption of electric vehicles (EVs) among private car buyers. Motivated by incentives for environmental sustainability and energy security, both the central and local governments in major cities have implemented a series of policies aimed at encouraging the replacement of gasoline vehicles (GVs) with EVs.

2.1.1 Two Primary EV Policies in Beijing

Among these major cities, Beijing, one of the largest local vehicle markets in China, has implemented two primary demand-side policies to encourage the adoption of EVs.

Local EV Subsidies. The municipal government of Beijing has been implementing local subsidy programs for EVs since 2010 to encourage EV purchases through financial incentives. From 2014 to 2015, the local government offered private buyers of eligible EVs a cash rebate of 45,000 RMB (approximately 7,223 USD). The eligibility of EVs for this rebate was determined by the local government through a specific whitelist. During this period, the subsidies provided by the local government accounted for 22.5% of the average listed prices of EVs[1].

There were also other local subsidy programs varying across cities in terms of their timing and magnitude. For instance, the Shanghai government offers a subsidy of 30,000 RMB for plug-in hybrid EV purchases and 40,000 RMB specifically for battery EV purchases. In contrast, the Beijing local government focuses primarily on battery EVs and provides the highest local subsidies available.

The Green License Plate (GLP) Policy. In addition to subsidy programs, the Beijing municipal government has established a separate license application system that provides additional EV license quotas for EV buyers under the binding license quota policy for regular license plates[2]. This quota-related EV policy is referred to as the green license plate policy in China (the GLP policy) because the government issues distinctive green-colored

[1]The Beijing government published a whitelist called the "Catalogue of Beijing Demonstration Application of New Energy Passenger Vehicle Manufacturing Enterprises and Products" to specify which EVs qualified for the local subsidy program. Additional details about the whitelist can be found in Appendix I.

[2]The license quota policy aims to regulate the number of newly registered vehicles through a quota allocation system. Since its introduction in 2010, this quota system has been adopted in seven cities in China to limit vehicle usage. More details can be found in Section 2.1.2 and also in previous studies (Li 2018, Guo and Xiao 2022).

license plates to EV license applicants, while regular license applicants receive blue plates.

The GLP policy, which is similar to the license quota policy for regular license plates, set a quota for EV license plates. However, the EV quota was not binding during the sample period, allowing EV buyers to bypass the strict license quota system that applies to regular license plates in Beijing. According to the official website of the Beijing Transportation Bureau, the odds of winning an EV license plate in February 2014 were 100%, whereas the odds for a regular license plate during the same period were only 0.903%. The GLP policy in Beijing provided a straightforward and convenient way for EV buyers to acquire a license plate, significantly shortened the waiting periods for a new EV license plate compared to the complex and binding lottery system for regular license plates. This presented substantial incentives for EV adoption (Li et al., 2020).

Appendix A summarizes a timeline of EV policies in seven major cities in China. This paper specifically examines local subsidies and the GLP policy within the context of Beijing.

2.1.2 Background of EV Adoption Policies

China's Electric Vehicle Market. In 2010, China's electric vehicle (EV) industry was still in its early stages, with the EV market largely underdeveloped. By the end of 2010, only about 7,100 electric vehicles had been sold across the country. At that time, the market featured merely six plug-in hybrid EV models, and battery EV models were notably absent from the market.

With the introduction of policies designed to promote EVs and a strong political drive to advance the EV industry, annual EV sales surged dramatically, reaching 946,294 by the end of 2020, with hundreds of EV models available on the market. Over the decade, the penetration rate of EVs increased from 0.04% to 4.81%.

Central EV Subsidies. The Chinese central government launched the first phase of a national cash incentive scheme for EVs from 2010 to 2014. This initiative offered private EV buyers 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 vehicle attributes. A second phase of the subsidy program began in September 2013 and continued until December 2015. This phase provided reduced subsidies of 30,000 to 40,000 RMB (about 4,615 to 6,154 USD), again based on the characteristics of the vehicle. The central subsidy amounts are included in my study and treated as constant for analysis.

The License Quota Policy. Over the last three decades, China has experienced rapid growth in the number of private cars. While this surge in vehicle ownership has made transportation more convenient for the public, it has also led to environmental and traffic challenges, including congestion and air pollution, particularly in major cities like Beijing and Shanghai. To address road congestion issues and improve air quality, seven city councils in China implemented a trial program to limit vehicle usage. Between 2010 and 2015, Beijing, Shanghai and five other cities [1] established a policy that imposed restrictions on the number of new registered vehicle licenses, known as the license quota policy (or vehicle quota system).

Among the seven cities, Beijing has adopted a non-transferable lottery system to allocate license plates since January 2011. The lottery allocation was conducted monthly before January 2015 and bi-monthly thereafter, occurring at the beginning of each month. Individuals who win the lottery are permitted to register their vehicles with the allocated license quota. According to the official records from Beijing, the annual quota for license plates was around 240,000 from 2011 to 2013, and was reduced to 105,600 after 2013. The limited availability of license quotas, combined with an increasing demand for new vehicle registrations, has led to a significant decline in the odds of winning a license plate in Beijing. Specifically, the odds dropped from 6% in February 2011 to an all-time low of 0.65% in 2015. Due to the stringent license quota policy, it can take years for a first-time buyer in Beijing to obtain a new license and register their car (Qin et al., 2021). As documented by Xiao, Zhou and Hu (2017) and Li (2018), the license quota policy has played an important role in controlling the total number of cars on the road[2].

2.2 Data

My analysis relies on five main data sets.

The first dataset I use comes from vehicle registration records in China, covering all registered vehicles across 34 cities, including provincial capital cities like Beijing and municipalities, from 2010 to 2015. I compiled the registration records into quarterly trim-level

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

[2] Appendix B provides further details for the license quota policy.

vehicle sales for each market, defined as a city during a specific quarter. Each observation in the dataset represents a product-level vehicle model within the given market.

The second dataset applied in my analysis is the vehicle product information data, which comes from the Chinese vehicle registration records. This dataset includes detailed characteristics of all observed vehicles at a trim level. The variables in this dataset encompass the manufacturer's suggested retail price (MSRP), vehicle manufacturer (e.g., BYD Auto), vehicle brand (e.g., BYD Qin), vehicle model type (e.g., Qin Plus), as well as width, height, length. Additionally, it includes information on fuel consumption, vehicle segment, fuel type, and more.

The third dataset comprises microdata on electric vehicle (EV) consumers' second-choice preferences in 2015, obtained from the China Electric Passenger Vehicle Consumer Survey Report (2015). This survey, conducted across the country in 2015, reports the average proportion of EV consumers who would have chosen EVs had their current choice been unavailable.

The fourth dataset used in my analysis consists of license application information, which I collected from the official website published by Beijing Municipal Commission of Transport. This dataset includes the total quota allocated for both regular and EV license plates, the total number of applicants in the regular and EV license application systems, and the total number of winners who did not utilize the regular license plate quota. Additionally, I derive the winning odds of the lottery system for each period from the data. Note that the lottery for license allocation in Beijing occurs on a monthly or bi-monthly basis, I aggregated the quota and applicant numbers into quarterly data.

The fifth data set I utilize is aggregate household information obtained from China's national household survey. This data includes the total population and the vehicle ownership rate in each market. It helps us determine the market size and identify the type of vehicle consumers.

3 Effects of the GLP Policy and EV Subsidies

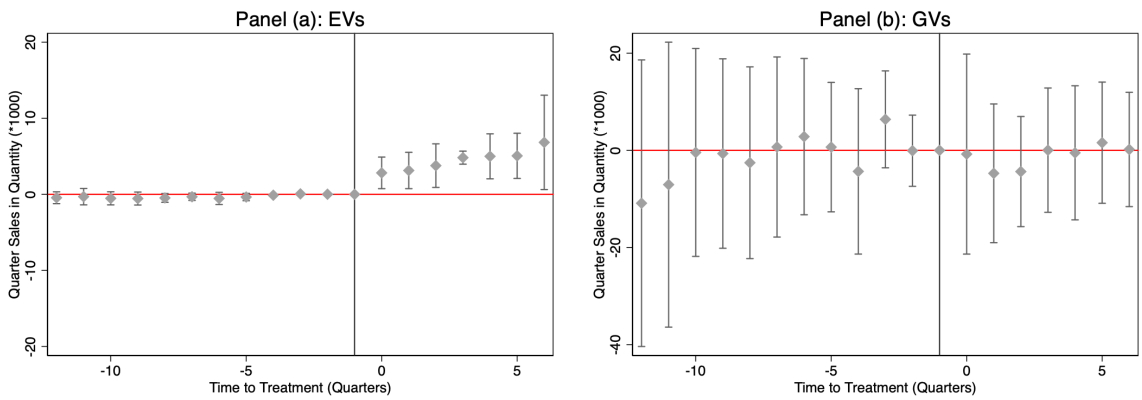
To check how the GLP policy affects EV sales, I first examine the effects of the GLP policy on quarterly sales of EVs and GVs using an event study design. The specification is as follows:

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

where Y_{gmt} represents the outcome measure, defined as the total number of sales of group g (EVs or GVs) in city m during quarter-year t. G_m is an indicator variable that takes the value 1 for treatment cities that have implemented the GLP policy (e.g. Beijing) and 0 for the control cities that have never adopted the GLP policy. T_k denotes an indicator variable for the k^{th} quarter-year relative to the implementation time of the GLP policy. X_{gmt} is a vector of control variables, including EV subsidies, the total number of quotas, and the number of vehicle models available in city m at time t. $\eta_{m\times year}$ and η_t denote the fixed effects for city-year and quarter-year, 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: Effect of the GLP Policy on Total Sales: Event Study



Notes: *The figure displays the effects of the GLP policy on total quarterly sales of EVs and GVs in China. It plots the regression coefficients for the policy change, along with their 95 percent confidence intervals, as derived from equation 1. The effects are normalized to the end of the quarter immediately preceding the policy. Standard errors are clustered at the city level.*

Figure 1 shows the average treatment effects of the GLP policy, captured by the interaction term ($G_m \times T_k$). It plots the estimated coefficients with 95 percent confidence intervals for the total sales amount of EVs in Panel (a), and the total sales amount of GVs in Panel (b). I find that none of the pre-policy coefficients (a_k with $k < 0$) for the sales of EVs and GVs are statistically significant, which suggests parallel trends between the treatment and control cities before the GLP policy. After the GLP policy was enacted, there was a significant increase in the total quarterly sales of EVs, and this impact persisted for at least one year and a half. During the first six quarters following the policy implementation, average total sales of EVs in the treatment cities rose by $4,514$ units each quarter. In contrast, the sales of GVs did not show any significant changes after the GLP policy.

In addition to the event study analysis, I investigate the impacts of EV subsidy and the 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 that have implemented the GLP policy. It takes the value of 1 if city m adopted the GLP policy during or after month-year t, and 0 otherwise. D_{mt} is an interaction indicator for the treatment cities with local subsidies. It is equal to 1 if city m initiated the local subsidy program during or after month-year t, and 0 otherwise. X_{gmt} refers to a vector of control variables, including indicators for the license quota policy, the total number of available products in group g, and a constant. The regression analysis includes fixed effects for both city and month-year, represented by the terms η_m and η_t, respectively. The coefficients b_1 and b_2 capture the average treatment effects of the GLP policy and EV subsidies on the sales of EVs and GVs, respectively. Here, $(e^{b_1}-1)$ and $(e^{b_2}-1)$ provide the percentage change in the sales observed after the local government announced the GLP policy and the subsidy program, holding all other variables constant. A larger value of b_1 suggests a stronger impact of the GLP policy on the sales of group g, while a larger value of b_2 indicates a more significant effect of EV subsidies on the sales of group g.

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 sales for EVs and GVs, respectively.

Table 1: DID Regression Result

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 presents the regression coefficients and standard errors for the policy changes based on equation 2. The data includes 34 cities over 72 months from 2010 to 2015. The treatment cities are Beijing, Tianjin, Shanghai, Hangzhou, Guangzhou, Shenzhen, and Guizhou.*

As the benchmark specification in my analysis, the coefficient estimate in Column (1) for the GLP policy (b_1) suggests that average EV sales increased by 227.1% ($e^{1.186} - 1$) after the government announced the GLP policy, holding all other variables constant. The coefficient estimate for the EV subsidy program (b_2) indicates that total monthly EV sales increased by 176.5% ($e^{1.017} - 1$) 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 EV subsidies on total 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 primary concern regarding the robustness of the results is the assumption of parallel trends. To alleviate this concern, I test the sales differences between the treatment group and the control group before the policies with an event study design and find no significant differences in the sales of EVs and GVs.

Another possible concern is about the assumption of a constant average treatment effect across different groups over time. It is possible that the treatment effects of the policies are heterogeneous across the multiple treatment cities over time. To address this concern, I analyze the compositional changes in the treatment cities and evaluate the new estimator proposed by de Chaisemartin and D'Haultfœuille (2020). The results remain consistent, suggesting that the GLP policy and EV subsidies have significant positive impacts on EV adoption.

There are also concerns regarding the network externalities associated with EV charging stations. The construction of these stations may bring positive network effects to the development of the EV market, potentially leading to an overestimation of the impacts of EV policies. However, in this study, the network effects of EV charging stations are not considered a major concern, as home charging was one of the primary methods of charging electric vehicles during the sample period from 2010 to 2015.

The regression analysis indicates the effects of both EV policies on total sales of EVs and GVs. However, to examine how EV policies affect consumer purchase and firm pricing behaviors as well as welfare, a structural model is required for policy analysis.

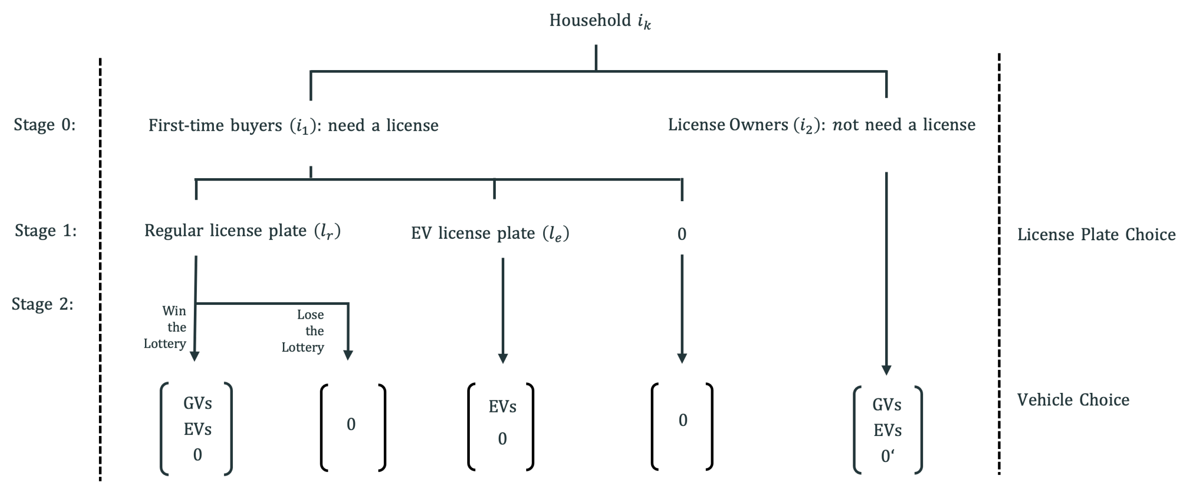
4 Structural Model

In this section, I build a structural model to analyze the policy impacts through consumer and firm responses. The model features a discrete choice system that endogenizes both consumer license plate selection and vehicle choice incorporating consumers demographic heterogeneous preferences on the demand side. I then explain the firms' responses using 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 timing is illustrated in details as following:

Figure 2: Model Timeline



License Ownership (Stage 0). Stage 0 depicts the nature of the market. In Stage 0, there are two types of consumers in the population with a total size of M_{mt} in 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 market m at time t and there are no dynamic choices among the consumers at this stage. 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 currently does not own a car or possess a license plate when the quota policy is implemented. She needs to acquire a new license plate in Stage 1 in order to register a new vehicle in Stage 2.

For a license owner i_2, she currently owns a car and a license plate when the quota policy is implemented. She can scrap her used vehicle[1] and use the existing license to register a new vehicle. Since she does not need to acquire a new license plate to register her car, she can bypass the decision process in Stage 1 with a regular license plate. In Stage 2, she can select her new vehicle from the full choice set, denoted as $\{0, \mathcal{J}_{GV}, \mathcal{J}_{EV}\}$. Here, $\mathcal{J}_{GV}$ represents the set of all available GVs. $\mathcal{J}_{EV}$ is the set of all available EVs. 0 denotes the option of not making a purchase.

Note that the two groups of consumers cannot be distinguished as we do not observe individual-level data of consumer type. Following the practice of Li (2018), I assume the vehicle ownership rate (o_{mt}) represents the probability of being a license (vehicle) owner in market m at time t. While this assumption may seem restrictive, it closely reflects reality, as the quota policy implementation in Beijing is an exogenous shock to consumers. Given this assumption, the consumer types in the model can be characterized using 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 expressed 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 with consumer vehicle choice in Stage 2 and then move to consumer license plate choice in Stage 1.

Stage 2: Consumer Vehicle Choice

Stage 2 models consumer choices for vehicles following the framework of Berry, Levinsohn and Pakes (1995) and Grigolon and Verboven (2014). At the beginning of Stage 2, first-time consumers know the result of the license lottery, which can be either "win the lottery" or "lose the lottery". Both first-time consumers and license owners then make their vehicle purchase decisions by choosing their most preferred car model j from the given choice set.

I model the indirect utility $u_{i_k jmt}$ of consumer i_k ($k = 1, 2$) for vehicle product j in

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

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 independent consumer product-specific shock that follows a type I extreme value distribution. Specifically, I assume that the product-specific shock $\epsilon_{i_k jmt}$ is realized at the beginning of Stage 2.

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 and central subsidies for product j in market m at time t. d_{jmt} is the amount of subsidy for product j in market m at time t provided by the local 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, which equals to 1 if $j \in \mathcal{J}_{\text{EV}}$ and 0 otherwise. $\nu^{EV}_{i_k mt}$ captures the unobserved consumer taste for the EV characteristic, which follows a standard normal distribution with the standard deviation of 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, which takes the value of 1 if $k = 1$ and 0 otherwise. γ_1 captures the consumer type-specific utility towards vehicle purchase. For identification, the type-specific utility of consumer i_2 is normalized to be 0. Here, γ_1 address the fact that first-time consumers are more determined to purchase a vehicle than the license owners as they do not currently own a car. γ_1 is identified from the observed shares of first-time buyers not making a vehicle purchase after winning the lottery in Stage 2. Except the consumer type-specific parameter γ_1, my model assumes that the first-time consumers and license owners have the same preference parameters. [1]

Stage 1: Consumer License Plate Choice

Stage 1 models consumer choices for license plate types and explains how the quota system works. In Stage 1, a first-time buyer (i_1) who does not currently own a license plate decide to go through the license application process. She has three options: applying for a regular license to participate in the lottery allocation process, applying for an EV (green) license plate, or choosing not to apply for any license plate.

I denote the first-time consumer i_1's choice of license plate types as $l \in \{l_r, l_e, 0\}$ where l_r corresponds to a regular license plate; l_e represents an EV (green) license plate and 0 is the option of not participating.

To reflect the fact that the GLP policy requires EV license plate applicants to select only among EV models, the license plate type choice made by first-time consumers' in Stage 1 forms a constraint on their choice set for vehicles in Stage 2. Specifically, if she applies for a regular license plate and wins the lottery, she can choose from the full choice set given by $\{0, \mathcal{J}_{\mathrm{GV}}, \mathcal{J}_{\mathrm{EV}}\}$. However, if she applies for a regular license plate and loses the lottery, her vehicle choice set is limited to be $\{0\}$. If the consumer i_1 selects an EV license plate (l_e) in Stage 1 and obtains the plate through the GLP policy, she could choose from a constrained choice set of vehicles given by $\{0, \mathcal{J}_{EV}\}$. The relationship between the license plate type

[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 given more available consumer-level information.

choice in Stage 1 (l_{i_1}) and the vehicle choice set ($\Omega_{l_{i_1}}$) in Stage 2 can be written as follows:

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

Given that consumer's license plate type choice corresponds to their vehicle choice set and there is no additional value of owning an unused license plate as resale or transfer of license plates is not allowed, I write the value V_{i_1lmt} for a first-time consumer i_1 obtaining the license plate type l in market m at time t as

$$V_{i_1lmt} = \ln\Big[\sum_{j\in\Omega_l} \exp(\delta_{jmt} + \mu_{i_1jmt})\Big], \tag{8}$$

where V_{i_1lmt} 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 constrained by the license plate type choice l, as depicted in equation (7). δ_{jmt} and μ_{i_1jmt} denote the mean and heterogeneous utility of consumer i_1 consuming product j in the market m at time t, respectively.

It's important to clarify the assumptions and functional forms of consumer valuation of license plate types. First, I assume consumers base their choice of license plate on the utility of all available options in their vehicle choice set, which are determined by the set of vehicle products they can purchase rather than a specific product. This setup is valid in my model because the timing of events dictates that a consumer makes their license plate type choice in Stage 1 before their individual product-specific taste shock for each vehicle μ_{i_1jmt} is realized. Therefore, they consider all available options in the vehicle choice set, rather than the most preferred choice, when determining their valuation for each license plate type. Although this assumption may seem non-trivial, it is not as restrictive as it appears; it is consistent with common purchase behavior, where buyers choose among a group of car products (e.g. EVs) before picking a specific vehicle product.

Second, the idea of using the logit inclusive value of the corresponding vehicle choice set as the value for a license plate type l draws inspiration from Gowrisankaran and Rysman (2012). The functional form of the logit inclusive value captures consumers' endogenous selection for license plate type choice based on their heterogeneous preferences. For instance, the model accounts for the observed fact that consumers who prefer EVs are more likely to choose EV license plates, leading them to self-select into the EV license application process.

The assumption about how consumers value license plate types is critical in formulating this decision problem as a two-stage decision process. Without this assumption, households have to make joint decisions on their license plate type choice and vehicle 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 license plate types V_{i_1lmt} from their vehicle preferences in Stage, and 2) simplifying the decision process of license plate types to be a trade-off between the expected valuation of the relevant choice set and the expected cost of applying for the license type l.

The utility for first-time consumer i_1 choosing 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 market m at time t. V_{i_1lmt} is consumer's valuation of the license plate of type l in market m at time t. In equation (9), c_l captures the application cost of obtaining license type l, which 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 license application cost comes from the observed shares of consumers choosing each type of license plate among the total population in market m at time t. ϵ_{i_1lmt} denotes the *i.i.d.* random taste shock for consumer i_1 for license type l in market m at time t, which follows the type I distribution. For identification, the utility $\bar{U}_{i_10mt}$ of i_1 consumer not participating in the license lottery process is normalized to be 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} denotes the total number of quotas for the license plate type l established by the local government in market m at time t. Q_{lmt} represents the total number for applicants in market m at time t. The expected odds of winning the lottery for license type l equals to 1 if the quota system is not binding (e.g. EV license quota system). If the quota system is binding, it equals $\frac{q_{lmt}}{Q_{lmt}}$. This framework allows for flexibility in capturing unexpected policy changes within the quota system (e.g., the announcement by Beijing in October 2015 to provide free EV license plates to all applicants in the EV license plate allocation system). Here, I assume consumers hold rational expectations over the odds of winning license plates, and that 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 product-specific random taste shock $\epsilon_{i_k jmt}$, the choice probability of consumer i_k for product j conditional on their owning license type l is

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

where $Z_{i_k jmt}$ includes unobserved consumer-specific heterogeneous taste $\mu^{\mathrm{EV}}_{i_k mt}$. $\Omega_{l_{i_k}}$ is vehicle choice set constrained by license plate type 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 $l_{i_2} = l_r$ associated with the full vehicle choice set $\Omega_{l_r} = \{0, \mathcal{J}_{GV}, \mathcal{J}_{EV}\}$.

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

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

where ρ_{lmt} is the odds of winning the lottery for license type l in market m at time t defined by equation (11). $\overline{U}_{i_1 lmt}$ is the expected utility of consumer i_1 obtaining the license plate

l that captures consumer's utility for obtaining all the available options corresponding to license plate choice l as well as the application cost of license type l. For consistency, the license plate choice probability of a license owner i_2 is written as $\mathbb{Pr}_{i_2lmt}(l_{i_2} = l_r) = 1$.

With the choice probabilities, I generate the aggregate demand for product j in market m at t. Given the model setup, the market share s_{jmt} of product j is

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

where $\mathbb{Pr}_{i_kjmt}(.|\text{with } l_{i_k})$ is vehicle choice probability defined by equation (12). $\mathbb{Pr}_{i_klmt}(.)$ denotes license plate choice probability defined by equation (13).

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

$$\begin{aligned} s_{jmt} = & \underbrace{\int [\mathbb{Pr}_{i_1jmt}(.|\text{with } l_{i_1} = l_r) \times \mathbb{Pr}_{i_1l_rmt}(.) \times \rho_{l_rmt} \times \mathbf{Pr}_{i_1}]dF(Z_{i_1jmt})}_{\text{(i) shares from first-time consumers } i_1 \text{ who win the regular license plate lottery}} \\ & + \underbrace{\int [\mathbb{Pr}_{i_1jmt}(.|\text{with } l_{i_1} = l_e) \times \mathbb{Pr}_{i_1l_emt}(.) \times \rho_{l_emt} \times \mathbb{Pr}_{i_1}]dF(Z_{i_1jmt})}_{\text{(ii) shares from first-time consumers } i_1 \text{ who obtain the EV license plate}} \\ & + \underbrace{\int [\mathbb{Pr}_{i_2jmt}(.|\text{with } l_{i_2} = l_r) \times \mathbb{Pr}_{i_2l_rmt}(.) \times \mathbb{Pr}_{i_2}]dF(Z_{i_2jmt})}_{\text{(iii) shares from license owners } i_2 \text{ who own regular license plates}}, \end{aligned} \tag{15}$$

where $\mathbb{Pr}_{i_1}$ and $\mathbb{Pr}_{i_2}$ are consumer type probabilities of being first-time consumers or license owners, respectively, as defined in equation (3).

As illustrated above, the model specification endogenizes consumer license plate choice and captures consumer demographic heterogeneity through the heterogeneous utility term μ_{i_kjmt} in consumer vehicle choice in Stage 2. As for the policies, the model integrates the quota policies (license quota policy and the GLP policy) via the quota numbers defined in the odds of winning the lottery for license plates in equation (11). Notably, the GLP policy implemented in Beijing during the sample period allows for unbinding EV license quotas, resulting in a 100% odds of winning an EV license plate. The model also incorporates the amount of subsidy using consumer-perceived prices in equation (5).

4.2 Supply Side

On the supply side, I assume auto manufacturers indexed by f engage in 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 prices for all vehicle products $\mathcal{J}^f_{mt}$ owned by their firm to maximize their profit. 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 price of product j in market m at time t determined by the auto manufacturer. Observed prices form a Nash equilibrium to the pricing game. J^f_{mt} is a set of all vehicles products owned by manufacturer f. mc_{jmt} is marginal cost of product j in market m at time t. I assume marginal cost, mc_{jmt}, associated with producing a vehicle j is a constant in each market m at time t. s_{jmt} is aggregate market shares of product j 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 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, such as entry or exit decisions, as well as changes in firms' strategies over time. If firms pursue strategies beyond merely maximizing their current profit, the marginal costs inferred by assuming a static Nash equilibrium in prices could be misleading. Alternative assumptions for firms' objective functions could be incorporated into further counterfactual analysis following the idea of Bresnahan (1987) and Guo and Xiao (2022). However, in this study, I focus on evaluating the static impacts of demand-side policies without attempting to measure supply-side dynamics.

4.3 Remarks on Policy Effects

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

(i) *Direct Price Effects.* My model captures the impact of EV subsidies by including the subsidy amount parameter d_{jmt} in the mean utility equation (5) on the demand side. The changes in the EV subsidy amount directly influence consumer-perceived prices for vehicles, which can affect the sales of EVs.

(ii) *Quota Effects.* In the two-stage discrete choice model, quota policies, including the license quota policy for regular license plates and the GLP policy for EV license plates, are represented by the quota number q_{lmt} in the lottery winning odds equation (11) and 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 and affect aggregate demand for EVs.

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

(iv) *Price Adjustment Effects.* The supply side of the structural model allows EV and GV producers to adjust prices in response to changes in EV policies. For example, the implementation of the GLP policy could potentially grant EV manufacturers greater market power by differentiating the EV market from the GV market, enabling them to set higher prices.

With the model estimated, I can recover 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 represents the mean preference parameters for vehicle characteristics in the mean utility equation (5), which is expressed as $\theta_1 = \{\bar{\alpha}, \bar{\kappa}, \beta, \eta_m, \eta_t, \xi_{\text{make}}\}$. θ_2

denotes the set of heterogeneous taste parameters in the consumer-specified utility equation (6) expressed as $\theta_2 = \{\sigma^{EV}, \gamma_1\}$. θ_3 is the set of application cost parameters for 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 (2004a) and Grieco, Murry and Yurukoglu (2023). My estimation procedure is implemented in two steps described as below. 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 δ towards all products where $\delta = \{\delta_j\}_{\mathcal{J}}$, consumer heterogeneous preference parameters θ_2 and consumers' license application costs θ_3. I denote the parameters to be estimated in the first step as $\Theta = (\delta, \theta_2, \theta_3)$. In the estimation, 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 second-choice micro-moments by matching predicted shares of EV consumers who choose EVs as their second choice, conditional on their current choice being unavailable with their empirical analogues. This set of micro-moments is crucial for identifying consumer preference heterogeneity for EVs.

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

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

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 $j \in \mathcal{J}_{\text{EV}}$, would still choose an EV product $h \in \{\mathcal{J}_{\text{EV}} \setminus j\}$ 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:

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

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 with product j being their most preferred option computed from the model. It can be written as

$$s_{h,j}(\Theta) = \int \mathbb{Pr}_{i_k hj}(\Theta, Z_{i_k j}|\text{with } l_{i_k}) \times \mathbb{Pr}_{i_k l}(\Theta) dF(Z_{i_k j}, \rho_l, i_k), \tag{20}$$

where $\mathbb{Pr}_{i_k l}(.)$ is license choice probabilities defined by equation (13). $\mathbb{Pr}_{i_k hj}(.|\text{with } l_{i_k})$ denote the joint choice probability of consumer choosing second-preferred product h with most preferred product j conditional on the status of having a license plate l_{i_k} , which can be computed as

$$\mathbb{Pr}_{i_k hj}(\Theta, Z_{i_k j}|\text{with } l_{i_k}) = \frac{\exp(\bar{u}_{i_k h})}{\sum_{h \in \{\Omega_{l_{i_k}} \setminus j\}} \exp(\bar{u}_{i_k h})} \cdot \frac{\exp(\bar{u}_{i_k j})}{\sum_{j \in \Omega_{l_{i_k}}} \exp(\bar{u}_{i_k j})} \tag{21}$$

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

By matching the observed data with the model predicted shares, the first set of micro-moments can be written as

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

Moment 2. The second set of micro-moment conditions is constructed based on the observed and predicted shares of not making a purchase among winners of regular license plates from the license application information. This helps identify the first-time consumer-specific taste preference parameter. By matching the predicted shares of not making a purchase among winners of regular license plate to their empirical analogues observed in the data, I formulate the second set of 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 not making a purchase among winners of regular license plates. $\tilde{\mathrm{S}}(\Theta)_{0|i_1, \text{win } l_r}$ is the predicted shares of winners of regular license plate choosing not to purchase a vehicel as a function of Θ.

The observed shares $\mathrm{S}_{0|i_1, \text{win } l_r}$ of not making a 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 aggregate shares of first-time consumers choosing not to purchase a vehicle, conditional on they win the regular license plate. The expression is given by

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

where $\mathbb{Pr}_{i_1 0}(\Theta, Z_{i_1 j}|\text{with } l_{i_1} = l_r)$ is the choice probability of consumer i_1 choosing not to purchase a vehicle conditional on winning the regular license plate l_r, which can be expressed as

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

Moment 3. The third set of moments is formed based on the license application information collected from Beijing Municipal Commission of Transport. In the dataset, I observe the shares of first-time consumers applying for regular license plates and EV license plates among the population. To construct the moment condition, I compute the predicted shares $\tilde{\mathrm{S}}(\Theta)_{i_1 l}$ of first-time consumers i_1 choosing the license type l $(\in \{l_r, l_e, 0\})$ as a function of parameters Θ as

$$\tilde{\mathrm{S}}(\Theta)_{i_1 l} = \int \mathbb{Pr}_{i_1 l}(\Theta) dF(Z_{i_1 j}), \tag{26}$$

where $\mathbb{Pr}_{i_1 l}(\Theta)$ is license choice probabilities defined by equation (13).

By matching the predicted shares of first-time consumers i_1 choosing the license plate l $(\in \{l_r, l_e, 0\})$ to their empirical analogues, I get the moment conditions:

$$g_3(\Theta) = \mathbb{E}_t\big[\mathrm{S}_{i_1 l} - \tilde{\mathrm{S}}(\Theta)_{i_1 l}\big], \tag{27}$$

where $\mathrm{S}_{i_1 l}$ is the observed shares of first-time buyers choosing the license plate l from the license application data. The third set of moments is crucial for the identification of license application costs.

By stacking the three set of moments, I could construct simulated GMM estimators for (θ_2, θ_3) and pin down the consumer-specific heterogeneous taste parameters $\theta_2(= \{\sigma^{\text{EV}}, \gamma_1\})$

and the license type-specific application costs parameters $\theta_3 (= \{c_{l_r}, c_{l_e}\})$. I use a weight matrix based on the inverse variance matrix of the data moments.

For a given value of (θ_2, θ_3), I recover the vector of δ for each market with the contraction mapping algorithm referring to Berry et al. (1995). Specifically, I compute the predicted market shares $\tilde{s}_j$ for each vehicle product j in based on equation (14). Then I map the predicted shares for each vehicle to the observed market share data and solve for δ as a function of (θ_2, θ_3) as

$$\delta_j^{n+1} = \delta_j^n + \ln(\mathbb{s}_j) - \ln[\tilde{s}_j(\delta^n, \theta_2, \theta_3)], \tag{28}$$

where n is the number of iterations.$\mathbb{s}_j$ is a vector of observed market shares for product j. $\tilde{s}_j(\delta^n, \theta_2, \theta_3)$ is the function predicted market share for product j.

The estimation process starts with an initial guess of $(\delta^0, \theta_2^0, \theta_3^0)$, and a vector of simulated $\nu_{i_k}^{\mathrm{EV}}$. Then I iterate the mean valuations δ through the contraction mapping process $\hat{\delta} = \delta(\hat{\theta}_2, \hat{\theta}_3)$ and update (θ_2, θ_3) from the outer optimization until the minimum of the GMM objective function is achieved. In the process, θ_2 includes the consumer-specific taste parameters which enters the utility in a nonlinear way. θ_3 includes the license type-specific application cost parameters. I compute standard errors of (θ_2, θ_3) parameters using a bootstrap procedure.

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

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

where the variables are explained in equation (5). Note that there may be possible correlation of vehicle prices with the unobserved demand shocks e_{jmt}, potentially leading to endogeneity issue in the analysis. To address the concern and establish identification for prices, I build two sets of instrument variables for prices following Bresnahan (1987) and Berry (1994).

Instrument Variables for Prices. Based on the product characteristics, the two sets of IVs for vehicle prices are constructed as: 1) sum of exogenous characteristics of competing products in other firms denoted as $\sum_{h, h \notin \mathcal{J}_{mt}^f} X_h$,; and 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 where I assume the observed product characteristics, including 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. My identification is made possible through the assumption:

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

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

Market Size. I define the total market size as the total number of households in market m at time t denoted as M_{mt}. This assumption of drawing consumers from the same population follows the BLP literature (Berry et al., 1995; Berry et al., 2004a). It aligns with my setting as both the license plate application decision and the vehicle purchase decision is available to all qualified households in the market.

5.2 Parameter Estimates

Followin the estimation procedure, I estimate the demand side of my model. Table 2 presents the parameter estimates, showing a subset of the mean taste parameters θ_1 including $(\bar{\alpha}, \bar{\kappa}, \beta)$, the consumer-specific heterogeneous taste parameters θ_2 $(= \{\sigma^{\text{EV}}, \gamma_1\})$, and license application costs parameters θ_3 in order. I also include the city, year, and make-level fixed effects in the estimation procedure, but they are not depicted in the table for readability.

My estimation shows that the coefficient estimate $(\bar{\alpha})$ for vehicle prices is around -3.106, while the interaction between vehicle prices and income is 0.488. This implies that consumers on average have negative preferences towards prices, and those with a higher income exhibits less sensitivity to price changes.

Based on the estimates, the average own price elasticity of demand is calculated to be about -3.886. The magnitude of the price elasticities estimated in my model is comparable to previous studies using the same price specification (Berry et al., 2004b, Brenkers and Verboven, 2006; Albuquerque and Bronnenberg, 2012).

[1] The trim-level product attributes in our dataset ensure enough variations in the instrument variables even controlling for make-level product dummies ξ_{make}.

Table 2: Parameter Estimates

Variables	Coef.	S.E.
Parameters in θ_1		
Price ($\bar{\alpha}$) (*100,000 RMB)	-3.106	(0.234)
Price $\times$ Income	0.488	(0.004)
EV ($\bar{\kappa}$)	-6.517	(0.249)
Width	7.533	(0.348)
Length	1.634	(0.059)
Parameters in θ_2		
EV taste variations ($\hat{\sigma}^{\mathrm{EV}}$)	3.849	(0.102)
first-time consumer-specific taste ($\hat{\gamma}_1$)	7.208	(0.281)
Parameters in θ_3		
Regular license application cost ($\hat{c}_{l_r}$)	0.823	(0.052)
EV license application cost ($\hat{c}_{l_e}$)	0.912	(0.343)

Notes: *Table 2 displays the parameter estimates. In the first panel of this table, I estimate the parameters with an IV regression using vehicle registration data from 11 Chinese cities during 2010-2015. The total number of observations in the vehicle registration dataset is 188,723. The IV regression also includes the city, time, make-level fixed effects as well as the product characteristics (power, weight) that are not displayed in the table. In the second and third panel of this table, I use the microdata from the survey in 2015 and the license application information in Beijing during 2014-2015. The total number of observations in the license application dataset 7,831.*

The estimate of the mean taste for EVs ($\bar{\kappa}$) is -6.517, indicating that, on average, consumers have a strong negative preference towards EV products during the sample period, possibly due to range anxiety and concerns regarding EV technology in the early stages of EV adoption.

Additionally, I estimate a significantly large random coefficient $\hat{\sigma}^{\mathrm{EV}}$ for EVs, around 3.849, as shown in the second panel of Table 2, representing substantial heterogeneity in consumer tastes towards EV products. The estimate explains the strong substitution patterns observed in the second-choice data from the survey within EV consumers .

For reference, my estimate for the EV random coefficient, identified through the microdata in China in 2015, is comparable with the findings in Grieco et al. (2023), which used US automobile market data from 1980 to 2018. Moreover, my estimate for consumer heterogeneity in EV preference is notably larger than those presented in Xing et al. (2021), which used the US New Vehicle Customer Study during 2010-2014 and reported an estimate of 0.949 for alternative fuel-efficient vehicles.

The second panel of Table 2 also provides estimates for the consumer type-specific preference parameter regarding vehicle purchase, which is positive at 7.208. This implies that first-time buyers have a very strong inclination to purchase a vehicle once they win the regular license plate. The estimate is consistent with the fact that very few license winners choose not to make a vehicle purchase after winning the regular license plate, reinforcing the idea that first-time consumers are highly motivated to buy cars, as evidenced by their decision to apply for a license plate.

The third panel of Table 2 presents the estimated license application costs for obtaining a regular license plate or an EV license plate, which amount to approximately 0.823 and 0.912, respectively. These application costs reflect the psychological and financial burdens associated with the complex and time-consuming application procedures.

To better understand the magnitude of these application cost parameters, I compare them to the vehicle price parameter and calculate the one-time monetary costs associated with obtaining each type of license plate using the formula $\frac{\hat{c}_l}{\bar{\alpha}} \times 100,000$, where c_l denotes the estimated cost parameters for obtaining license type l. The results indicate that the one-time costs of acquiring a regular license plate and an EV license plate are relatively close, estimated at 26,497 RMB (approximately \$4,277) for the regular license plate (calculated as

$= \frac{0.823}{3.106} \times 100,000$) and 29,363 RMB (approximately \$4,713) for EV license plates (calculated as $= \frac{0.912}{3.106} \times 100,000$). For reference, the monetary license application costs estimated for regular license plates are comparable to the average one-time license fees paid by winner of the regular license plate in an auction system in Shanghai.

I also calculate the expected monetary costs of obtaining each type of license plate if consumers continue to apply until they win, using the formula $\frac{\hat{c}_l}{\bar{\alpha} * \hat{\rho}_l}$, where c_l denotes the estimated cost parameters and $\hat{\rho}_l$ denotes the average expected winning odds for the respective license type l. The findings reveal that the expected cost of securing a regular license quota until winning is exceedingly high, at 3,011,022 RMB (approximately \$483,310, calculated as $= \frac{0.823}{3.106 \times 0.0088} \times 100,000$) due to the low odds of winning the regular license plate lottery. Conversely, the expected cost of obtaining an EV license quota until winning is 29,363 RMB ($= \frac{0.912}{3.106 \times 1} \times 100,000$, approximately \$4,713), as the winning odds of an EV license plate are equal to 1.

To analyze the implied substitution patterns between vehicle products, I compute the product-level own- and cross-price elasticities. A sample of product-level price elasticities for selected EVs and gasoline vehicles (GVs) is presented in Table 6 found in Appendix C. This table in 6 illustrates that the product-level within-group cross-price elasticities of the selected EV products span from 0.0379 to 1.4443 while the EV-GV (cross-group) cross-price elasticities range from 1.06E-06 to 3.79E-05. These results suggest that EV products are relatively close substitutes for one another, whereas the substitutability between an EV product and a GV product is minimal during the sampled period.

To gain a comprehensive understanding of the substitution patterns within and cross the EV and GV groups, I calculate the average group-level cross-price elasticities within and across the vehicle groups using data from Beijing, 2014-2015. Here, the average group-level price elasticities within a group are defined as the average change in quantity of a typical product caused by a one percent price change of all other products in the group. The average group-level price elasticities across the groups (e.g. EV-GV) is defined as the average change in quantity of a typical product in the GV group due to price changes in EV products.

Table 3 shows that the mean product-level own price elasticities of EVs and GVs are around -5.2572 and -4.3403, respectively. This suggests that consumers are less price-sensitive

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

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

Notes: *I calculate the group-level price elasticities using the sample data in Beijing, 2014-2015. I define the average group-level price elasticities within a group as the average change in quantity of a typical product in that group when there is a 1% price change in all other products within the same group. Conversely, I define the average group-level price elasticities across groups (e.g., EVs and GVs) as the average change in quantity of a typical product in the GV group resulting from a 1% price change in all products in the EV group.*

to EV products compared to GVs during the sample period. The average cross-group price elasticity between EVs and GVs is about 0.0080, indicating that a 1% price decrease of all EV products would lead to an average of 0.80% decrease in the quantities sold of a GV product. According to Holland et al. (2021), the cross-price elasticity estimates suggest very low substitutability between EVs and GVs, with an average of less than 0.01 during the sample period. In contrast, the average group-level cross-price elasticity within the EV group is about 3.3555, indicating that EVs were close substitutes for each other during the sample period, consistent with previous findings.

The estimation results have several important implications. First, I find that consumers exhibit significant heterogeneity in their preferences for EV products. This suggests that EV policies could potentially have heterogeneous impacts on consumer vehicle purchase decisions. Second, while EVs served as close substitutes for each other within the same group, they were poor substitutes for GVs, indicating that EV poicies may have minimal impacts on the substitutions between EVs and GVs during the sample period.

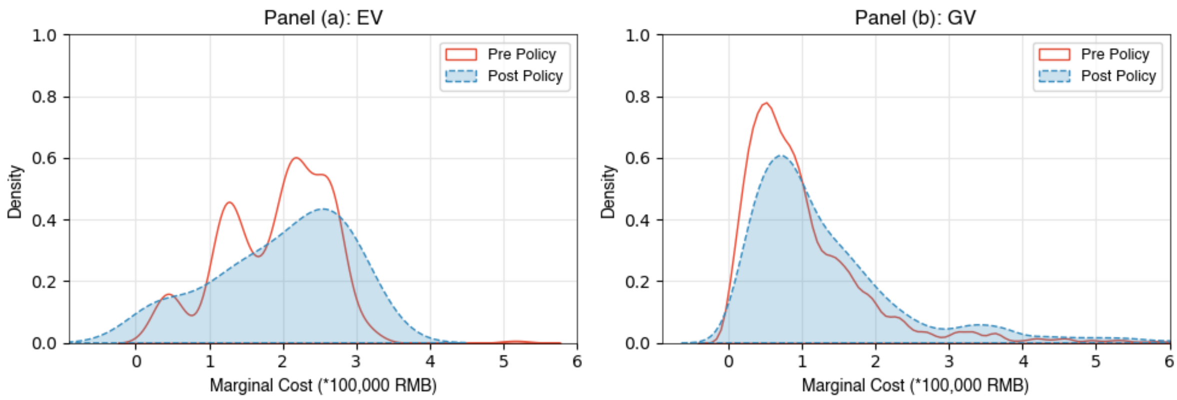
5.3 Model Fit

Table 7 in Appendix D presents the correlations between observed moments I target and the model predictions to demonstrate the model fit. In Table 7, I summarize the second-choice micro-moments from the microdata, the average shares of first-time consumers choosing not to purchase a vehicle, and the observed shares of regular license plate applicants and EV license plate applicants from the license application information. I also present the model-predicted values for these three sets of moments. As shown in Table 7, my estimated model matches the moments well.

5.4 Marginal Cost Estimates

Figure 3 illustrates the distribution of estimated product-level marginal costs. The average marginal cost of EVs in the sample data is 190,172 RMB ($30,525), while the average estimated marginal cost of GVs is 106,716 RMB ($17,129). This indicates that producing EVs is more expensive than producing GVs for manufacturers in the early stages, when the electric vehicle industry is still developing. Furthermore, the results show that the marginal cost estimates for EVs in the post-policy period of the GLP policy did not differ significantly from those in the pre-policy period, suggesting that EV production technology did not change substantially during the sample period.

Figure 3: Marginal Cost Distribution



***Notes**: The figure depicts the estimated marginal cost distribution for EV and GV models. The pre-policy marginal cost distribution is based on the sample from cities other than Beijing, while the post-policy distribution of marginal costs is drawn from the sample data in Beijing for 2014-2015.*

6 Policy Analysis

In this section, I use the model estimates to conduct counterfactual simulations to evaluate how EV subsidies and the GLP policy affect consumer purchase decisions, producer pricing behavior, and overall welfare outcomes. The counterfactual analysis is based on sample data from Beijing in 2015, a time when several EV producers were competing in the market and both policies were in effect.

For each vehicle product, I simulate market outcomes for the year 2015 based on three scenarios that assume different EV policies implemented by the local government. These scenarios are: (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 from the following two cases.

(ii) *only EV subsidies*: In this scenario, I assume the GLP policy has been removed, allowing first-time buyers to choose between regular license plate or no purchase when applying for a license plate.

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

For robustness, I keep the number of regular license quotas fixed in the counterfactual simulations and assume that the license quota policy remains unchanged. The techniques I use to conduct the counterfactual analysis are detailed in Appendix E. The setup allows us to decompose the impacts of EV subsidies and the GLP policy in both the EV and GV markets, enabling us to discuss the interactions between the two policies.

In the counterfactual results, I assume that changes in the policies lead to shifts in consumer purchase decisions and adjustments in producer pricing, holding consumer preference parameters and product-level 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 alternative EV policies by adjusting the current GLP policy and the amount of EV subsidies, 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 subsidies and the GLP policy implied by the model and I attempt to quantify.

Policy Effects on Sales. My model captures two potential effects of EV policies on EV demand. The first is the direct effect that these EV policies have on consumer utility through price or quota incentives, which is explained by the demand side of the model. For instance, a reduction in EV subsidies directly affect consumers' choices for EVs because of the cash rebate. Similarly, the implementation of the GLP policy could influence EV sales by providing additional EV license quotas offered to consumers. Increased EV quotas may enable more first-time consumers, who require license plates, to register new EVs.

The second effect involves the indirect influence of EV policies on producers' pricing strategies, which subsequently affects consumer choices through price adjustments. For example, in response to increased EV subsidies, manufacturers may raise EV prices, leading to a decrease in demand due to these price changes.

Additionally, there is a potential network effect of EV policies on the demand for EVs that my analysis does not capture: the demand dynamics effect. This effect refers to the dynamic impacts of higher EV demand. For instance, EV adoption policies may generate a network effect in which increased EV purchases contribute to the development of EV infrastructure, ultimately enhancing the utility of EVs in the future. Furthermore, demand-side policies could initiate a learning-by-doing effect, where the sale of EVs fosters learning, resulting in increased demand for EVs. In my analysis, I do not account for this dynamic demand effect, as my focus is primarily on the static impacts.

The estimated model also reveals the underlying substitution patterns between EVs and GVs, capturing how EV policies affect sales of both vehicle types. For instance, EV subsidies could encourage consumers to substitute GVs for EVs due to price effects.

Policy Effects on Pricing and Market Power. The model allows automakers to adjust vehicle prices in response to changes in EV policies. For example, an increase in EV subsidies to consumers might lead to higher EV prices, effectively passing the benefits of these subsidies to the automakers through their pricing strategies. The GLP policy may grant EV manufacturers greater market power to set higher prices, as it creates a distinct separation between the EV market and the GV market.

Policy Effects on Welfare Outcomes. Vehicle usage is closely linked to environmental externalities, including carbon emissions, air pollution, congestion, space, and crash costs. Deploying EVs is believed be to mitigate these issues by reducing the carbon emissions and pollution associated with traditional vehicles (Holland et al., 2016; Mitropoulos, Prevedouros and Kopelias, 2017; Rapson and Muehlegger, 2024). My analysis quantifies the welfare outcomes of EV subsidies and the GLP policy by evaluating changes in consumer surplus, producer profits, environmental externalities, and government expenditure linked to these policies.

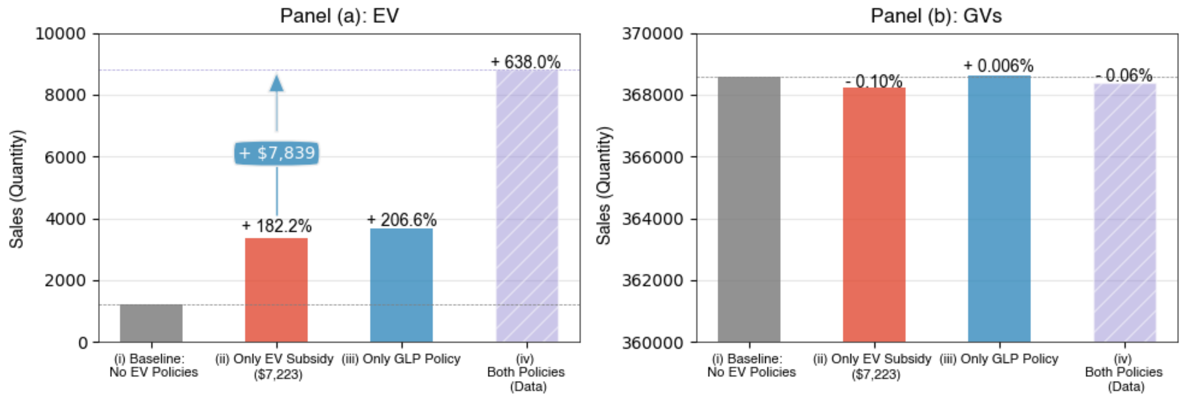
For the GLP policy implemented in Beijing, I assess its welfare outcomes by assuming it provides consumers with additional EV quotas within the binding license quota system while keeping the number of regular license quotas fixed. In this study, the market distortions caused by the regular license quota systems are not considered part of the welfare outcomes of the GLP policy. For reference, I separately quantify the market distortions and welfare outcomes related to the regular license quota system in Appendix G.

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 subsidies nor the GLP policy was implemented.

The counterfactual results presented in Panel (a) of Figure 4 show that if the government had not implemented the two primary demand-side EV policies (referred to 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, assuming all other conditions remain constant. Based on the baseline scenario, if the government had only offered the same amount of EV subsidies, total EV sales in Beijing in 2015 would have increased from 1,193 to 3,367, approximately 182.2% higher than the baseline scenario. If only the GLP policy had been implemented, the total number of EVs sold in Beijing would have reached 3,658, approximately 206.6% higher than the baseline scenario. These results suggest that both subsidies and the green license policy play a significant role

Figure 4: Counterfactual Sales Impacts



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

in promoting EV sales, highlighting their effectiveness in facilitating EV adoption.

Moreover, the total increase in EV sales in the case where both policies were implemented exceeds the combined sales increase from the counterfactual scenarios (ii) and (iii), suggesting the combination of EV subsidies and the GLP policy is more effective than implementing either policy alone while keeping costs fixed. This provides an important implication for policymakers: the two demand-side policies complement each other in promoting EV adoption.

Impacts on GV Substitution. Despite the substantial impact of EV sales, I find that EV subsidies and the GLP policy in our context have minimal impacts on the GV market. Scenario (ii) in Panel (b) of Figure 4 shows that the total GV sales would have decreased by only 0.10% relative to the baseline scenario (i), resulting in 385 fewer GVs sold, had the government introduced EV subsidies. This small decrease in GV sales, paired with a significant increase in EV sales in Scenario (ii), suggests that the subsidy policy mainly encouraged adoption among potential consumers who were previously not considering purchasing a vehicle. This outcome diverges from the policy's goal of encouraging substitution from GVs to EVs.

In terms of the GLP policy, had the government implemented it alone, total GV sales would have increased by 0.006%, equating to 22 more GVs sold, as illustrated in Scenario (iii) of Panel (b) in Figure 4. While this increase may seem counterintuitive, it is reasonable considering that EV prices would have been significantly higher compared to the baseline scenario if the GLP policy had been enacted. Consequently, some consumers who would have chosen EVs might opt for GVs due to the price effect.

Overall, the changes observed in the counterfactual scenarios indicate a weak substitution pattern between EVs and GVs due to the subsidy and the GLP policy in the context of Beijing, 2015. This finding aligns with our earlier 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 reveal the comparable and sizable impacts of both EV policies on promoting EV sales. Given the minimal cost associated with implementing the GLP policy (considered to be the cost of distributing a distinctive green license plate for EVs), it's natural to ask: how much money does the GLP policy save the government in the deployment of EVs? To answer the question, I simulate the additional amount of subsidies per EV that would be necessary to replace the GLP policy while maintaining the number of deployed EVs at the observed level (8,804 EVs) based on the counterfactual scenario (ii) in the sample data from Beijing, 2015.

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

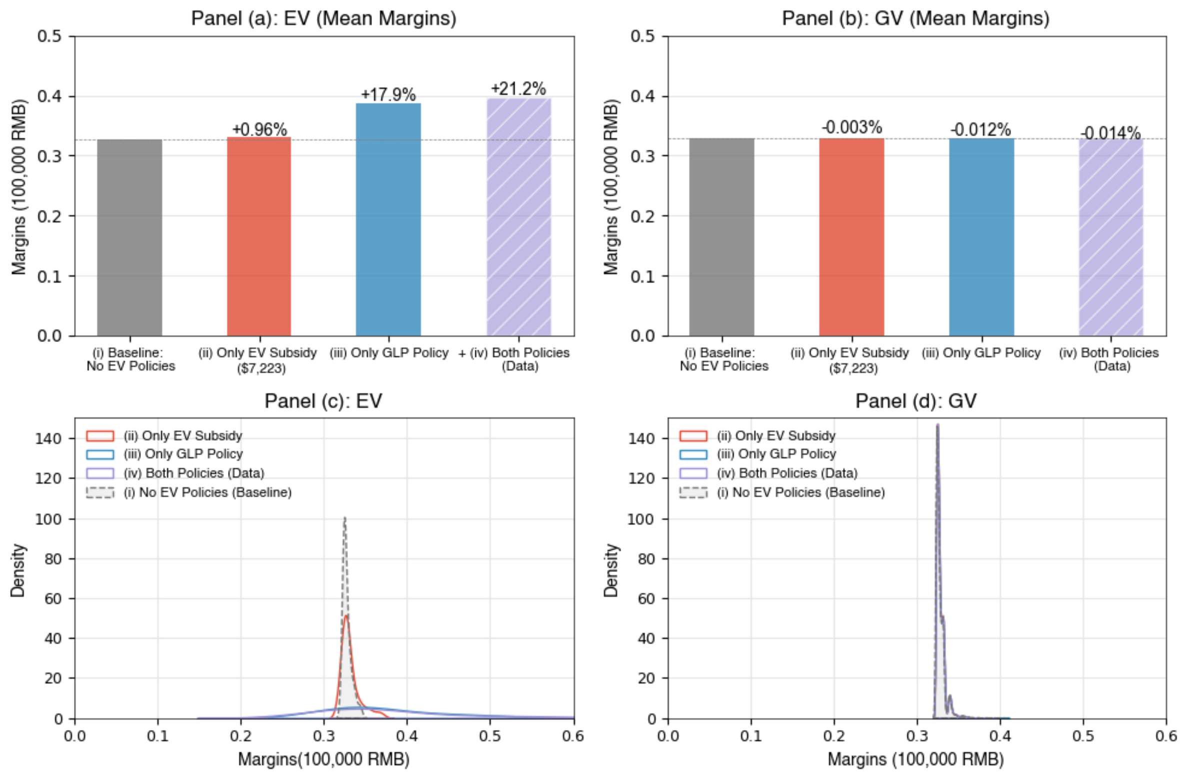
In total, the Beijing local government spent \$63.59 million on EV subsidy programs in 2015. The implementation of the GLP policy saved the government \$69.01 million (\$7,839 $\times$ 8,804) in deploying EVs, which accounts for 27.60% of the government budget for EV subsidy programs. These results imply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

My analysis thus far demonstrates how these policies affect consumer purchasing behaviors regarding EVs and GVs, addressing the following policy questions: How many EVs does each policy deploy on the road? How many GVs were replaced by EVs under the EV policies? What is the subsidy equivalent of the GLP policy? Next, I will discuss 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 distribution of EVs margins and GVs margins simulated in the three counterfactual scenarios alongside data from Beijing's auto market in 2015. Here, margin (denoted as $p - mc$) is defined as the vehicle price minus the marginal cost, which measures the adjustments in auto manufacturers' pricing strategies, as 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 alongside data (iv) both policies in effect 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 average EV margins would have been around $5,262.3

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

without the implementation of any EV policies 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, which provides $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 shown in Panel (c) of Figure 5 indicates that the margins of EVs exhibit larger variations in the counterfactual scenarios (iii) and (iv), where the GLP policy is in effect, compared with the scenarios (i)(ii). The result implies that EV manufacturers have greater pricing power with the implementation of the GLP policy.

The price impacts of the GLP policy are novel but not entirely surprising, as the GLP policy separates the EV market from the GV market, thereby offering some protection to EV manufacturers from competition with GV manufacturers. This finding has crucial implications: while the GLP policy is cost-effective, it 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 minimal impact on the margins of GV producers, suggesting that these EV policies did not lead to significant changes in the pricing strategies of GV producers, holding all other variables constant.

As shown in Panel (d) of Figure 5, GV manufacturers did not significantly adjust their prices in response to the EV policies, consistent with our estimations indicating that the substitutability between EVs and GVs is relatively low during the sample period.

The GLP Policy and EV Market Structure. 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 (Beijing, 2015[1]) to those in a market with a single EV producer (Beijing, 2014[2]). For comparison, I calculate the Lerner indices (defined as $\frac{p_j - mc_j}{p_j}$) to measure 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,

[1]In 2015, there were seven EV manufacturers producing eight products in Beijing.

[2]In 2014, there was a single EV manufacturer (Beijing Automotive Group Co.) producing two products in Beijing.

and maximum) of EVs and GVs. Panel (a) illustrates the counterfactual EV markups in a market with multiple (seven) EV manufacturers competing in prices. The average (unweighted) markup of EVs would have been 0.1944 if neither of the EV policies had been implemented. 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 scenario. If only the GLP policy had been adopted, the average markup would have increased to 0.2146, representing a 10.38% increase over the baseline. With both policies in place, the average markup was around 0.2190, which is 12.61% higher than the baseline scenario. The results regarding EV markup are consistent with my previous finding that the implementation of the GLP policy enhances the market power of EV producers in a market with seven EV manufacturers.

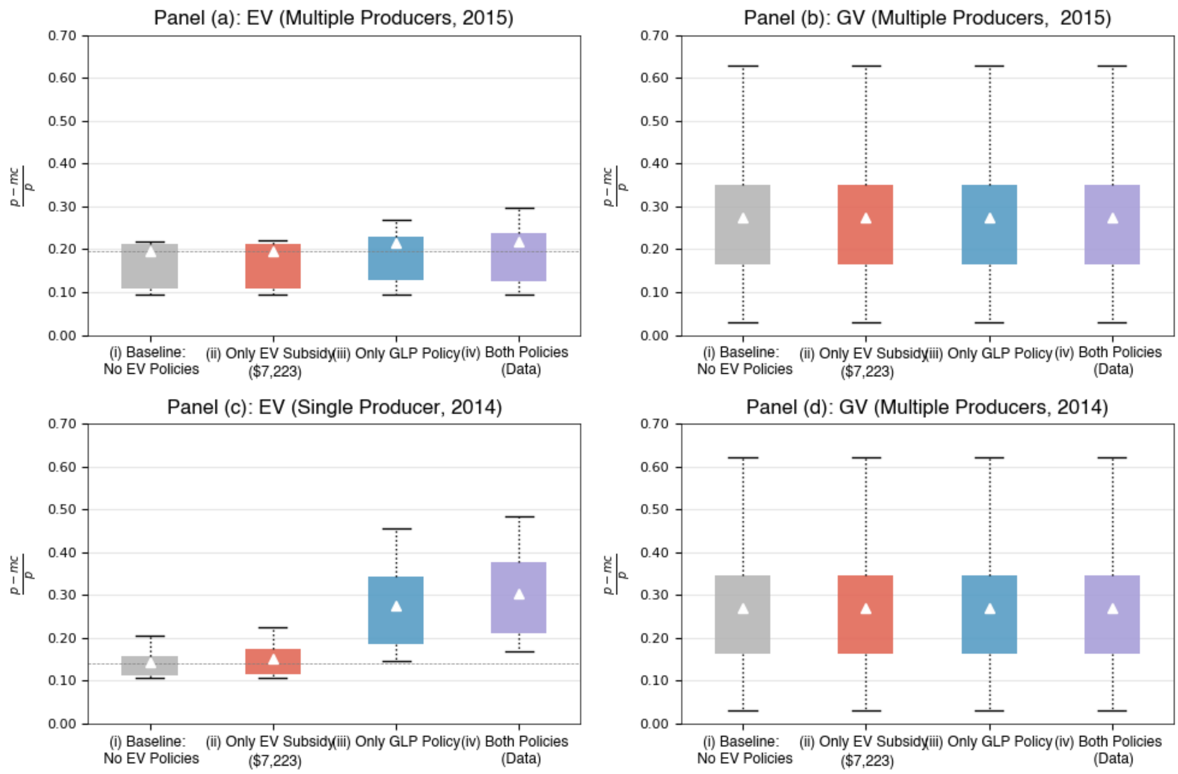
Panel (c) in Figure 6 presents the average counterfactual markup of EVs in a market dominated by a single EV manufacturer in Beijing in 2014. From the data, I find that the average (unweighted) markup was approximately 0.3052 in Beijing in 2014, which is relatively high for the auto market, as documented in Berry et al. (1995). If the government had only implemented the GLP policy, the average markup would have been 0.2769, reflecting a reduction of 9.26% compared to the data. Had the government implemented the subsidy program alone, the average markup would have been 0.1519, representing a reduction of 50.22% relative to the data. If neither of the EV policies had been implemented, the average markup of EVs would have been 0.1428 with a decline of 53.24%.

The results support my previous findings and suggest that market structures significantly affect the evaluations of EV policies. In a market with only one EV manufacturer producing EVs, the GLP policy resulted in high market power for EV producers, ultimately harming consumers due to elevated EV prices.

Panel (b) and (d) in Figure 6 show that the average markup of GVs were around 0.2750 in Beijing in 2015 and 0.2707 in Beijing in 2014. The markup remained relatively stable across the counterfactual simulations and over time. This 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 clarify how the GLP policy influences the impact of EV subsidies on producers' pricing strategies, I analyze the subsidy pass-through rate to EV producers both in the context with and without the GLP policy. The

Figure 6: Markups Distribution



***Notes**: The figure illustrates the product-level markup distributions (mean, median, interquartile range, minimum and maximum) of EVs and GVs using two sample data: Beijing,2014 and Beijing,2015. Panel (a) and Panel (b) display the markup distributions of EVs and GVs under the counterfactual scenarios and the data case 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.*

subsidy pass-through is a commonly used measure in public economics to reflect how subsidies are distributed between consumers and producers (Kelly 2014; Pless and Van Benthem 2019). In this paper, I define the subsidy pass-through as the rate at which subsidies are passed on to producers. It is written as $\frac{p^w - p^0}{d_w}$, where p^w is the equilibrium vehicle price in the counterfactual scenario w with subsidies where $w = (ii), (iv)$. p^0 is the competitive market equilibrium price simulated in the baseline counterfactual scenario (i) without subsidies; d_w denotes the amount of subsidy in the counterfactual scenario w. For this analysis, d_w is set to a constant value of \$7,223. The rate of subsidy pass-through to producers in this setting falls between 0 and 100 percent, with higher values (or lower values) indicating that a greater portion of subsidies benefit producers and lower values indicating that more benefits accrue to consumers. The graphical representation of the subsidy pass-through is provided in Appendix F.

The results indicate that the average (unweighted) pass-through rate to producers would have been approximately 1.35% in the counterfactual scenario (ii), where only EV subsidies were implemented. In the data case where both EV subsidies and the GLP policy were in place, the pass-through rate to producers was 25.72% suggesting 25.72% of EV subsidies were transferred to producers instead of being passed on to consumers due to the GLP policy. Especially, in a market dominated by a single producer (Beijing, 2014), the average (unweighted) subsidy pass-through rate to producers was 5.74% without the GLP policy, but it surged to 137.13% with the GLP policy in place, indicating an over-than-complete transfer of subsidies to producers when the GLP policy was implemented.

The findings regarding producer price responses provides critical insights for the implementation of subsidies and the GLP policy aimed at promoting EV adoption:

First, EV manufacturers may increase prices and secure higher profits following the implementation of EV subsidies or the GLP policy in a market with few competitors. Consequently, if manufacturers adjust their strategies in response to these EV policies, the primary objectives of benefiting consumers and encouraging EV adoption could be compromised.

Second, my analysis advises policymakers to proceed with caution when implementing the GLP policy alongside subsidies. The GLP policy markedly affects the extent to which subsidies are passed on to EV producers, despite its substantial impact on increasing EV sales.

Third, I find that the GLP policy greatly enhances the market power of EV manufacturers. This underscores the necessity for policymakers to consider the structure of the EV market when evaluating the GLP policy.

6.4 Welfare Outcomes

Next, I examine the welfare outcomes of EV subsidies and the GLP policy, considering consumer surplus, producer surplus, government expenditures, and environmental externalities. Then, I compare the net welfare surplus of the two policies.

Consumer Surplus (CS). I employ the compensating variations (CVs) to measure changes in consumer surplus resulting from policy implementation. In my setting, I define compensating variations (CVs) as the additional monetary transfer required by a consumer i who are offered the product bundle in a counterfactual scenario w with the outside good valued at 0 relative to receiving only the option to purchase the hypothetical outside good 0. Given the model setup, the compensation variations $\overline{CV}^w$ for an average consumer - in the w^{th} scenario where $w = (i), (ii), (iii), (iv)$ can be written as,

$$\overline{CV}^w = \int_{i_k} \frac{1}{\bar{\alpha}} \left[\left(\ln \sum_{j \in \{0, \mathcal{J}^w\}} \exp(\delta_j^w + \mu_{i_k j}^w) \right) - \mu_{i_k 0}^w \right] dF(Z_{i_k j}, \rho_l, i_k), \tag{31}$$

where w indicating the counterfactual scenario where (i) baseline: *No EV policies*, (ii) *EV subsidies only*, (iii) *the GLP policy only*, and (iv) *both EV policies*. δ_j^w is the mean utility of the product j given the equilibrium prices in the w^{th} scenario. $\mu_{i_k j}^w$ represents the heterogeneous utility terms of consumer i_k for product j which includes the consumer-specific taste for EV products and their type-specific taste for vehicle purchase in the counterfactual w^{th} scenario. $\mu_{i_k 0}^w$ represents the consumer type-specific taste for not making a purchase. $\mathcal{J}^w$ denotes the product choice set determined by the counterfactual scenario w.

Then, the total consumer surplus $\overline{CS}$ in the w^{th} scenario is given by

$$\overline{CS}^w = M_w \overline{CV}^w, \tag{32}$$

where M defines the market size in the scenario w.

Producer Surplus (PS). I compute total variable profits of auto manufacturers as a measure of producer surplus. Given the prices and sales simulated from the counterfactual scenario w, I calculate total variable profits of auto manufacturers in the counterfactual market w as follows

$$\overline{PS^w} = \sum_f \pi_f^w = \sum_f \sum_{j \in \mathcal{J}_f} \left[(p_j^{w*} - mc_j)q_j^{w*}\right], \tag{33}$$

where p_j^{w*} is the equilibrium price for product j in the counterfactual scenario w. mc_j denotes the marginal cost of product j assumed to be constant in the counterfactual simulations. q_j^{w*} is the equilibrium sales quantity of product j in the counterfactual scenario w.

Government Expenditure (GExp). The government expenditure resulting from the EV policies is defined as the total amount of money that the government spend to implement the corresponding policy. For the subsidy program, the government expenditure equals the total amount of EV subsidies distributed during the sample period. For the GLP policy, the government expenditure is considered to be zero in the analysis, as the cost of distributing distinctive license plates is minimal.

Externalities (EC). EV adoption policies have potential effects on the environmental externalities. These externalities come from the EV-GV substitution led by the EV policies, which could reduce environmental external cost resulted from vehicle usage by shifting the auto consumption from GVs with higher emissions and pollution to EVs with lower emissions and pollution (Holland et al. 2016; Guo and Xiao, 2022). There can also be potential network externalities caused by the demand dynamics effect as I discussed in Section 6.1. In the welfare analysis, I focus on the environmental externalities, and do not account for the dynamic externalities to discuss the static welfare outcomes of these policies.

To measure the environmental externalities associated with the usage of GVs and EVs, I calculate the annual external costs associated with the usage of an EV or GV, accounting for five sources of external costs. These external costs include: carbon emissions and air pollution (affecting global warming and air quality), crash costs (for partner vehicles in multi-vehicle crashes), roadway congestion, and space consumption (Lemp and Kockelman, 2008). I summarize these five sources of external cost and assume the average annual external cost (AEC_{EV}) per EV per vehicle mile traveled (VMT) to be in the range of \$0.033-\$0.050 estimated by Mitropoulos, Prevedouros and Kopelias (2017). The average vehicle's external cost (AEC_{GV}) per GV per vehicle mile traveled (VMT) is estimated to be in the range of \$0.140-\$0.329 per VMT (Parry, Walls and Harrington, 2007). To avoid overestimation of the external cost due to vehicle usage, I use the median of the interval estimates as the inputs for AEC_{EV} and AEC_{GV} in the following calculation.

According to the *China Energy Conservation and New Energy Vehicle Development Annual Report (2017)*, the average vehicle miles traveled (VMT) per vehicle per year in Beijing in 2013 was around 10,876 miles (17,500 km). As the VMT per vehicle increases over time, I use the estimate of 10,876 miles as a lower bound for VMT for both EVs and GVs in Beijing in 2015.

Then, I multiply the factors above and calculate the annual external cost YEC_g led by the usage of a vehicle in group g ($\in \{EV, GV\}$) as

$$YEC_g = AEC_g * VMT * Q_g, \tag{34}$$

where Q_g denotes the total number of vehicles sold in the group g.

To quantify the total environmental externalities accrued by EVs and GVs across vehicle lifetime, I make assumptions about the time horizon over which the external costs accrue. Although a license plate could last through multiple vehicle usages, I assume the maximum average time horizon over which external costs accrue to be the average vehicle lifetime. This ensures that my analysis does not overestimate the environmental external costs associated with vehicle usage. In China, the maximum legal age for 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 lifetime of a GV 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 lifetime of usage for an EV in 2014 is around 7-8 years. Given the assumption on the minimum time horizon of vehicle usage, I assume the average vehicle lifetime to be 7 years for both EVs and GVs.

Then, the total external cost (TEC) due to vehicle usage across their lifetime is

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

where YEC_g represents the annual external cost led by total vehicles in the group g. LS_g is the estimate of the vehicle lifetime for the vehicles in group g.

Net Welfare Surplus. By summing up consumer surplus, producer surplus, government expenditure and externalities, I compute net welfare surplus in the vehicle market.

As my calculation estimates the lower bound of environmental external costs led by the vehicle usage, my analysis offers the lower bound of welfare impacts led by the EV policies.

Table 4 displays the welfare outcomes measured in millions of dollars in the counterfactual scenarios (i) baseline: *No EV policies*, (ii) *only EV subsidies*, (iii) *only the GLP policy*, and the data case (iv) both policies in effect.

Table 4: Welfare Outcomes

Scenario	Baseline (i)	(ii)	(iii)	(iv)
Beijing, 2015	*No EV Policies*	*Only EV Subsidies*	*Only the GLP Policy*	Both Policies
Regular License Quotas	105,600	105,600	105,600	105,600
EV License Quotas	-	-	20,000	20,000
EV Sales	1,193	3,367	3,658	8,804
GV Sales	368,600	368,215	368,622	368,373
Welfare (in a million of dollars)		Δ Relative to the Baseline (i)		
Consumer Surplus (CS)	6356.97	37.40	41.58	130.22
Producer Surplus (PS)	1965.24	10.22	20.14	62.02
EV Producers	6.93	12.53	20.08	63.53
GV Producers	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, mean)	7523.92	-1.96	7.13	15.97
Net Welfare Surplus	798.29	25.26	54.58	112.68
Net Welfare Surplus Changes (%)	-	+3.16%	+6.84%	+14.12%

***Notes**: The table displays the welfare outcomes of the three counterfactual scenarios (i)(ii)(iii) as explained above and the data case (iv) in the automobile market, measured in a million of dollars in the sample data period (Beijing, 2015). The external costs provide the mean estimates for environmental externalities resulted from vehicle usage based on assumption of average external cost and vehicle lifetime (7 years).*

The results in Table 4 indicate that the introduction of EV subsidies valued at $7,223 per EV leads to an increase of $37.40 million in consumer surplus due to the cash rebate. The implementation of the GLP policy increases consumer surplus by $41.58 million by providing consumers with extra EV quotas while keeping all other factors constant. When both the subsidies and the GLP policy are combined, consumer surplus rises by $130.22 million.

As for producer surplus, the welfare outcomes show that the EV subsidies leads to an increase in EV producer surplus of $12.53 million. In contrast, the GLP policy results in a more substantial increase of $20.08 million in EV producer surplus. This suggests that EV producers earn higher profits under the GLP policy as it reduces competition by separating the gas vehicle (GV) and EV markets through a distinctive license plate quota system. Both policies result in minimal changes in GV producer surplus, as they have insignificant impacts on GV prices and sales.

To better understand how welfare surplus is distributed among consumers and producers under the EV policies, I calculate the ratio of consumer surplus to the sum of consumer and producer surplus, represented as $\frac{CS}{CS+PS}$. The calculation reveals that consumer surplus accounts for 78.6% of the total when only the EV subsidies are implemented, and 67.4% when only the GLP policy was in effect. This indicates that under the GLP policy, a larger share of the welfare gains benefits EV producers, whereas the subsidy results in a distribution that favors consumers. This finding aligns with previous findings that the GLP policy enhances the market power of EV producers through market separation.

As shown in Table 4, the government expenditure in the sample data where both the subsidy and the GLP policy were applied amounted to about $63.59 million. If only the EV subsidies had been implemented, the government expenditure on the subsidy program would have been around $24.32 million. In contrast, the expenditure on the GLP policy was negligible, as it involved minimal costs for distributing distinctive license plates.

The externalities shown in 4 indicate the mean estimated external costs associated with vehicle usage. The implementation of EV subsidies produces modest welfare gains in terms of environmental externalities, amounting to $1.96 million due to the substitution of EVs for GVs. However, the adoption of the GLP policy results in a welfare loss of $7.13 million in environmental externalities, driven by increased EV usage resulting from additional EV quotas.

By aggregating consumer surplus (CS), producer surplus (PS), government expenditures (GExp), and considering the minimum external cost (EC), I find that the EV subsidies lead to a net welfare surplus increase of approximately $25.26 million, representing a

3.16% increase compared to the baseline. In contrast, the GLP policy increased net welfare surplus by $54.58 million, equivalent to a 6.84% increase compared to the baseline. This finding highlights the cost-effectiveness of the GLP policy in comparison with the EV subsidy program implemented in Beijing in 2015.

Furthermore, I find that the combination of the GLP and the subsidy policy generates a significant net welfare surplus increase of $112.68 million, which is a 14.12% increase relative to the baseline case in the context of Beijing in 2015. This implies substantial positive welfare impacts from the combined policy of the EV subsidies and the GLP policy within the auto market.

6.5 Alternative Policies With Adjusted Quotas and Subsidies

In addition to evaluating the welfare outcomes of current policy practices in Beijing, I discuss the potential welfare impacts of alternative policies by adjusting the current GLP policy and analyzing the optimal amount of subsidies in the specific context of Beijing, 2015.

Alternative GLP Policy by Reserving EV Quotas. As previously mentioned, I propose an alternative GLP policy through which the government reserves EV quotas from the existing regular license plate quota system instead of distributing additional EV quotas to consumers. This approach keeps the total number of license plate quotas (regular license quota and EV license quota) fixed. Compared to the current GLP policy, this alternative approach could potentially yield environmental benefits by reducing the number of regular license plate quotas, thereby decreasing the usage of gasoline vehicles (GVs), which better addresses the rationale of encouraging EV-GV substitution. However, it could also lead to increased deadweight loss due to market distortions resulting from less regular license plate quotas.

Table 5 presents the welfare outcomes of the alternative GLP policy compared to other scenarios, with the total number of license quotas held constant. Unlike the setup in Table 4, the number of regular license quotas has been adjusted to 125,600 rather than 105,600 in the baseline counterfactual scenario (i) and (ii) in Table 5.

As shown in Table 5, the alternative GLP policy would decrease GV sales by 21,379 (from 390,001 to 368,622) and increase EV sales by 2,699 (from 959 to 3,658) relative to the baseline scenario with *no EV policies*. In contrast, the current GLP policy implemented in

Table 5: Welfare Comparisons with Alternative GLP Policy

Scenario	Baseline (i)	(ii)	(iii)	(iv)
Beijing, 2015	*No EV Policies*	*Only EV Subsidies*	*Only the GLP Policy*	Both Policies
			Alternative GLP	*Alternative GLP*
Total License Quotas (Fixed)	125,600	125,600	125,600	125,600
Regular License Quotas	125,600	125,600	105,600	105,600
EV License Quotas	-	-	20,000	20,000
EV Sales	959	3,472	3,658	8,804
GV Sales	390,001	389,493	368,622	368,373
$ in millions		Δ Relative to Baseline (i)		
Consumer Surplus (CS)	6712.08	42.40	-313.54	-224.89
Producer Surplus (PS)	2084.35	11.35	-98.97	-57.09
EV Producers	5.16	14.42	21.36	65.30
GV Producers	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, mean)	7959.95	-3.57	-428.90	-420.06
Net Welfare Surplus	836.48	32.24	16.39	74.49
Net Welfare Surplus Changes (%)	-	3.85%	1.96%	8.91%

Notes: *The table outlines the welfare outcomes of the counterfactual scenarios: (ii) only EV subsidies, (iii) only the alternative GLP policy, and the data where (iv) both subsidies and the alternative GLP policy were in effect, in comparison with the baseline (i) with no EV policies. In the counterfactual scenarios (i) and (ii), I consider a total of 125,600 regular license quotas (105,600 + 20,000), different from the previous setup with 105,600 regular license quotas in Table 4. The welfare results are presented in millions of dollars for the sample data period in Beijing in 2015.*

Beijing increased GV sales by 22 (from 368,600 to 368,622) and increased EV sales by 2,465 (from 1,193 to 3,658), as illustrated in Table 4. These results show that the alternative GLP policy is more effective in limiting GV usage and promoting EV-GV substitution compared to the current GLP policy.

Regarding welfare surplus, the alternative GLP policy would lead to a substantial decrease in consumer surplus by $313.54 million and a decrease in producer surplus by $98.97 million compared to the baseline scenario. Specifically, EV producers would experience an increase in producer surplus by $21.36 million, while GV producers incur a loss in producer surplus by $120.33 million under the alternative GLP policy. The results occur because the alternative GLP policy reduces the number of regular license quotas by reserving EV quotas, which distorts the market and leads to deadweight loss.

For the environmental externalities, the results indicate that the alternative GLP policy would result in significant environmental gains, with a mean value of around $428.9 millions, accounting for 5.39% relative to the baseline scenario. This benefit arises from the reduction in GV usage and the EV-GV substitution. Moreover, the analysis suggests that this alternative policy would generate a positive net welfare surplus of $16.39 million implying that the environmental gains from the policy would outweigh the deadweight loss due to quota constraints, based on a mean estimate for the environmental externalities in the context of Beijing in 2015.

Overall, my analysis demonstrates the alternative GLP policy, which reserves EV quotas from regular license quotas, is highly effective in curbing GV usage and encouraging EV-GV substitutions relative to the current practices in Beijing. From a policymaker's perspective, this alternative approach could enhance net social welfare, even under conservative estimates of environmental externalities.

Optimal Subsidy. In addition to examining the alternative GLP policy, I analyze the optimal amount of EV subsidies in conjunction with the GLP policy, aiming to maximize net welfare surplus in the auto market while considering the marginal cost of government expenditure specific to Beijing. Note that the trade-off associated with the EV subsidies involves balancing the marginal benefit of consumer surplus, producer surplus, and potential environmental gains from EV-GV substitution against the marginal cost of government spending. To be consistent with previous analysis, the net welfare surplus is written as:

$$Net\ Welfare\ Surplus = CS + PS - EC - \lambda \cdot GExp\ , \tag{36}$$

where CS and PS denote consumer surplus and producer surplus, respectively. EC represents the mean estimates for environmental externalities. $GExp$ is the total amount of government expenditure. λ is a factor that captures the marginal funding cost of government expenditure.

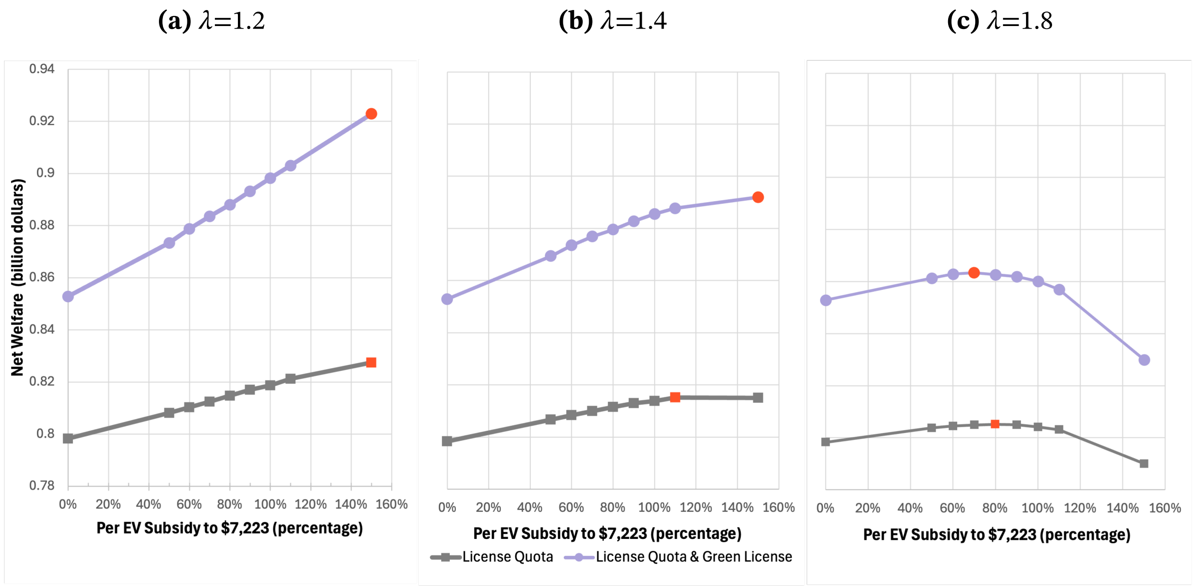
Specifically, I follow Nakamura and Steinsson (2014) and define the factor λ as the *fiscal multiplier*, which indicates the percentage cost in aggregate output resulting from raising government expenditure equivalent to 1% of GDP. According to previous studies (Nakamura and Steinsson, 2014; Guo, Liu and Ma, 2016; Chen, Ratnovski and Tsai, 2017; Gu and Lyu, 2023), estimates for the fiscal multiplier ranges from 1.2 to 1.8 across various context. Notably, Chen, Ratnovski and Tsai (2017) estimates the *fiscal multiplier* as 1.4 for China between 2010 and 2015.

In my study, I estimate the optimal subsidy amount within the context of Beijing in 2015, assuming the *fiscal multiplier* (λ) to be 1.2, 1.4, or 1.8. To ensure the optimal subsidy amount is feasible, I limit the available subsidy range to 0-150% ($0-$10,834) of the current subsidies ($7,223). A cash rebate exceeding 150% ($10,834) could surpass the lowest EV prices. Figure 7 illustrates the net welfare surplus results for the three values of the *fiscal multiplier*.

The figure indicates that with a funding cost factor of 1.2, the optimal subsidy should be at least 50% higher than the current subsidies (more than $10,834) to maximize net welfare surplus, regardless of whether the GLP policy was implemented. This suggests that increasing investments in EV subsidies could yield greater welfare efficiency in the auto market, particularly if the government's funding cost is low.

When the funding cost factor is 1.4, the optimal subsidy under the GLP policy is at least 50% higher than the current subsidies (more than $10,834), while the optimal subsidy without the GLP policy is approximately 110% of the current subsidies (around $7,945). This implies that, under medium funding costs, the optimal subsidy amount with the GLP policy could be higher than that without it as the GLP policy complements the subsidy, resulting in a larger marginal welfare surplus of subsidies compared to a situation where the government solely implements the EV subsidy program.

Figure 7: Optimal Subsidy Amount For Three *Fiscal Multipliers*



Furthermore, with a higher funding cost factor ($\lambda = 1.8$), the optimal subsidy amount under the GLP policy is 30% lower than the current subsidies (approximately \$5,056), while the optimal subsidy amount without the GLP policy is 20% lower than the current subsidies (approximately \$5,778). This indicates the cost-effectiveness of subsidies when interacting with the GLP policy under high funding costs.

As I do not observe the exact value of the local government's funding cost factor in Beijing, designing the optimal subsidy for policymakers under the GLP policy is beyond the scope of this analysis. However, my findings provide critical implications, suggesting that the optimal subsidy amount largely depends on the marginal funding cost of government expenditure. Additionally, the GLP policy could enhance the welfare impacts of subsidies regardless of the funding cost. Particularly with very high funding costs, the GLP policy could help the government save a substantial amount of money by reducing the optimal subsidies.

6.6 Caveats

For the reference of policymakers, I address two caveats warranted for the analysis in this paper. First, I focus on the static impact of EV policies on the demand side and do not account for the dynamic effects of EV adoption, such as network effects. The setup is appropriate in my analysis, as the EV market was still in its early stages during the data sample data period (2010-2015), when the relative share of EVs compared to GVs was around 0.24% in Beijing. Given the small number of EV users at that time, the network effect in this context may be negligible. However, the indirect network effect associated with a growing number of EV users in the auto market could potentially lead to an underestimation the policy impacts over time. Second, my model assumes static Nash-Bertrand pricing on the supply side. This assumption excludes considerations such as EV technology spillovers, industry upgrading, and dynamic pricing strategies employed by firms. For example, firms may increase their investment in research and development (R&D) for EV technology in response to EV adoption policies. In this scenario, the effects of EV policies on market outcomes could be significantly more positive than what my analysis indicates.

7 Conclusion

Over the last decade, electric vehicles (EVs) have attracted increasing attention from policymakers due to their potential to transform transportation. A variety of EV policies have been instituted in key markets, stimulating a major expansion of EV markets. Using a structural model for vehicle demand and supply and analyzing via numerical simulations calibrated to the auto market in Beijing, I examine the impacts of two primary demand-side EV policies, EV subsidies and the green license plate (GLP) policy, while also propose alternative policy options.

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

Moreover, my model estimation reveals that the substitutability between EVs and GVs was low during the sample data period. Consequently, my counterfactual analysis demonstrates that both EV subsidies and the GLP policy in Beijing had limited impacts on encouraging consumers to substitute GVs with EVs, which contrasts the primary stated rationale for these policies. My analysis also shows that, despite its minimal cost, the GLP policy could lead to significant market power for EV producers by segmenting the EV and GV market. This highlights the importance of accounting for market structure in policy evaluations within the auto market.

Most importantly, there are several aspects of this analysis that can be extended or policymakers concerned with EV adoption policies.

First, although quotas in the auto market may seem extreme and have not yet been part of the policy discussion surrounding EVs, my results suggest that implementing the alternative GLP policy which reserves EV license quotas from a regular license quota system could yield net welfare gains under certain conditions. This is particularly relevant for economies facing significant environmental externalities from 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 established, merely providing distinctive license plates to EV buyers may appear costless. However, it could inadvertently lead to unexpectedly high market power for EV producers, resulting in market distortions given the competitive market environment. Therefore, cautions concerning market structures should be exercised when evaluating demand-side EV policies.

Third, my study discusses the optimal level of subsidies in conjunction with the GLP policy to maximize net welfare surplus, which offers a more flexible perspective in designing demand-side EV adoption policies in the auto market.

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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 cities announced the license quota policy, the GLP policy, and the time when the government started to distribute central or local subsidies. There are some other policy benefits for EV users not listed above. For instance, EV users can enjoy unlimited parking rights in Beijing and Shanghai.*

B License Quota Policy and Allocation Systems

B.1 Beijing

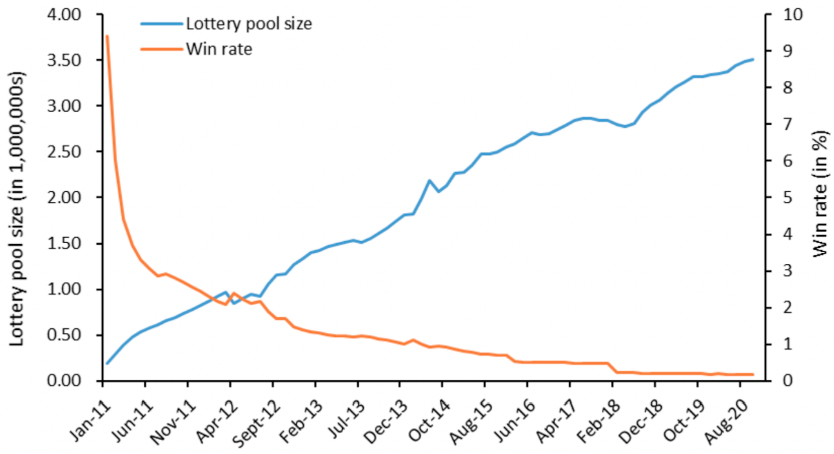
As the car ownership keep increasing from 2006, traffic congestion and air pollution become more and more severe in large cities. To address these two issues, municipal governments started to enact the policy of capping new licenses plates for GVs and issuing green license plates for EVs.

License Quota. The Beijing municipal government introduced a license quota system to cap the number of new vehicle registrations on December 23, 2010. A lottery system has been adopted since 2010, distributing approximately 20,000 licenses monthly between 2011 and 2013, with the annual quota reduced to 105,600 in 2014 and 2015. The policy applies mainly to first-time vehicle buyers. Owners replacing a scrapped vehicle can reassign their existing license to a new vehicle, bypassing the need for a new license. License plate transfer or resale is not allowed under the policy.

Lottery Allocation. The licenses are assigned to winners through random drawings under the quota system in Beijing. The winners can then use the license to register their vehicles. The winners are determined in the license lottery pools allocated monthly in 2014 and bi-monthly in and after 2015. 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 8 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 8: The Size of Beijing Lottery Pool and Lottery Winning Odds (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. This prevents buyers 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

Auction 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.

Average Bid. 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.

B.3 Other Cities

License Allocation. Besides the lottery application system in Beijing and the auction allocation system in Shanghai, there are others five cities including Hangzhou, Tianjin, Guangzhou, Shenzhen, and Guangzhou which adopted the license quota system and used a mixed allocation system with both lottery and auction to allocate the license quotas.

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

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

Brand	**Price**	BYD	Gelly	Volkswagen	Ford	Honda	Hyundai	Mazda	Chevrolet	Toyota	Audi	Infiniti	Mercedes-Benz	Chery	Zotye	JAC	Toyota	BYD
Make	**(RMB)**	F0	Jyoting SC7	Santana	Focus	Civic	Tussan	Speed6	Captiva	Prius	A4L	Q50	E320L	eQ	ZDD2	HeyueiEV	Camry	Tang
BYD F0	50,456	-1.5586	7.20E-06	1.17E-04	4.07E-05	1.14E-04	1.54E-05	4.70E-05	5.29E-05	1.07E-04	3.56E-05	1.75E-05	1.21E-04	5.37E-05	7.57E-05	1.07E-03	7.06E-04	8.59E-05
Gelly Jyoting SC7	36,197	6.20E-05	-1.1181	1.13E-04	3.97E-05	1.11E-04	1.51E-05	4.62E-05	5.32E-05	1.08E-04	3.60E-05	1.83E-05	1.35E-04	5.19E-05	7.45E-05	1.06E-03	7.12E-04	8.75E-05
Volkswagen Santana	112,133	5.02E-05	5.67E-06	-3.4637	3.54E-05	1.00E-04	1.41E-05	4.32E-05	5.47E-05	1.13E-04	3.79E-05	2.22E-05	2.16E-04	4.43E-05	6.90E-05	9.97E-04	7.35E-04	9.44E-05
Ford Focus	121,415	4.86E-05	5.50E-06	9.80E-05	-3.7505	9.85E-05	1.39E-05	4.27E-05	5.49E-05	1.14E-04	3.82E-05	2.29E-05	2.32E-04	4.32E-05	6.81E-05	9.87E-04	7.38E-04	9.54E-05
Honda Civic	131,436	4.69E-05	5.32E-06	9.60E-05	3.41E-05	-4.0600	1.37E-05	4.23E-05	5.52E-05	1.15E-04	3.86E-05	2.37E-05	2.50E-04	4.20E-05	6.72E-05	9.76E-04	7.41E-04	9.66E-05
Hyundai Tuscan	155,034	4.32E-05	4.93E-06	9.15E-05	3.26E-05	9.31E-05	-4.7890	4.12E-05	5.59E-05	1.17E-04	3.94E-05	2.56E-05	2.99E-04	3.93E-05	6.49E-05	9.49E-04	7.48E-04	9.95E-05
Mazda Speed6	160,581	4.23E-05	4.84E-06	9.04E-05	3.23E-05	9.22E-05	1.33E-05	-4.9603	5.61E-05	1.18E-04	3.96E-05	2.61E-05	3.11E-04	3.87E-05	6.44E-05	9.43E-04	7.50E-04	1.00E-04
Chevrolet Captiva	237,675	3.22E-05	3.76E-06	7.74E-05	2.81E-05	8.14E-05	1.22E-05	3.79E-05	-7.3418	1.27E-04	4.30E-05	3.39E-05	5.43E-04	3.08E-05	5.69E-05	8.53E-04	7.82E-04	1.13E-04
Toyota Prius	253,658	3.05E-05	3.57E-06	7.50E-05	2.73E-05	7.94E-05	1.20E-05	3.73E-05	5.97E-05	-7.8354	4.38E-05	3.58E-05	6.06E-04	2.93E-05	5.54E-05	8.35E-04	7.93E-04	1.17E-04
Audi A4L	256,479	3.02E-05	3.54E-06	7.46E-05	2.71E-05	7.91E-05	1.19E-05	3.72E-05	5.98E-05	1.30E-04	-7.9226	3.62E-05	6.18E-04	2.90E-05	5.51E-05	8.31E-04	7.95E-04	1.18E-04
Infiniti Q50	366,479	2.07E-05	2.51E-06	6.12E-05	2.28E-05	6.79E-05	1.08E-05	3.43E-05	6.60E-05	1.49E-04	5.06E-05	-11.3205	1.24E-03	2.03E-05	4.70E-05	7.44E-04	9.79E-04	1.73E-04
Mercedes-Benz E320L	587,607	1.11E-05	1.44E-06	4.64E-05	1.80E-05	5.60E-05	9.86E-06	3.19E-05	8.23E-05	1.96E-04	6.74E-05	9.69E-05	-18.1476	1.38E-05	6.20E-05	1.13E-03	2.90E-03	6.44E-04
Chery eQ	69,800	1.94E-05	2.18E-06	3.75E-05	1.32E-05	3.72E-05	5.15E-06	1.57E-05	1.85E-05	3.75E-05	1.25E-05	6.04E-06	2.78E-05	-0.7051	0.0995	1.4443	1.0554	0.1325
Zotye ZDD2	152,800	1.51E-05	1.73E-06	3.21E-05	1.14E-05	3.25E-05	4.63E-06	1.43E-05	1.83E-05	3.79E-05	1.27E-05	6.88E-06	3.39E-05	0.0542	-3.2351	1.3965	1.1042	0.1446
JAC HeyueiEV	169,800	1.43E-05	1.64E-06	3.10E-05	1.11E-05	3.16E-05	4.53E-06	1.40E-05	1.83E-05	3.79E-05	1.27E-05	7.05E-06	3.41E-05	0.0527	0.0935	-2.4740	1.1120	0.1472
Toyota Camry	259,800	1.06E-05	1.24E-06	2.54E-05	9.17E-06	2.65E-05	3.90E-06	1.21E-05	1.74E-05	3.67E-05	1.23E-05	7.54E-06	1.72E-05	0.0433	0.0830	1.2482	-6.8867	0.1635
BYD Tang	300,000	8.97E-06	1.06E-06	2.24E-05	8.13E-06	2.36E-05	3.52E-06	1.10E-05	1.63E-05	3.47E-05	1.17E-05	7.31E-06	8.23E-06	0.0379	0.0758	1.1527	1.1405	-9.0943

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

D Model Fit

Table 7: Model Fit

	Time	Data	Model	Diff
Moment 1				
Second-choice shares as EVs of EV consumers	2015	0.6600	0.6597	-3.00E-04
Moment 2				
Shares of not purchasing among regular license winners	2014-2015	0.0204	0.0203	-4.44E-05
Moment 3				
Shares of first-time buyers being regular license applicants	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
Shares of first-time buyers being EV license applicants	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 survey data among EV consumers in 2015. Moment 2 and Moment 3 are based on Beijing license application and 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.*

E Empirical Methods for Counterfactual Analysis

In this appendix, I present the technique details in the empirical method for the counterfactual analysis presented in Section 7.

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 GLP policy attract more consumers to EVs, thereby possibly motivating firms to introduce more EV models. If this is the case, my 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 separate impacts of the EV subsidy and the GLP policy by simulating scenarios where each policy is removed one by one. Then, I simulate consumers' purchase behaviors and firms' pricing in response to these policy changes.

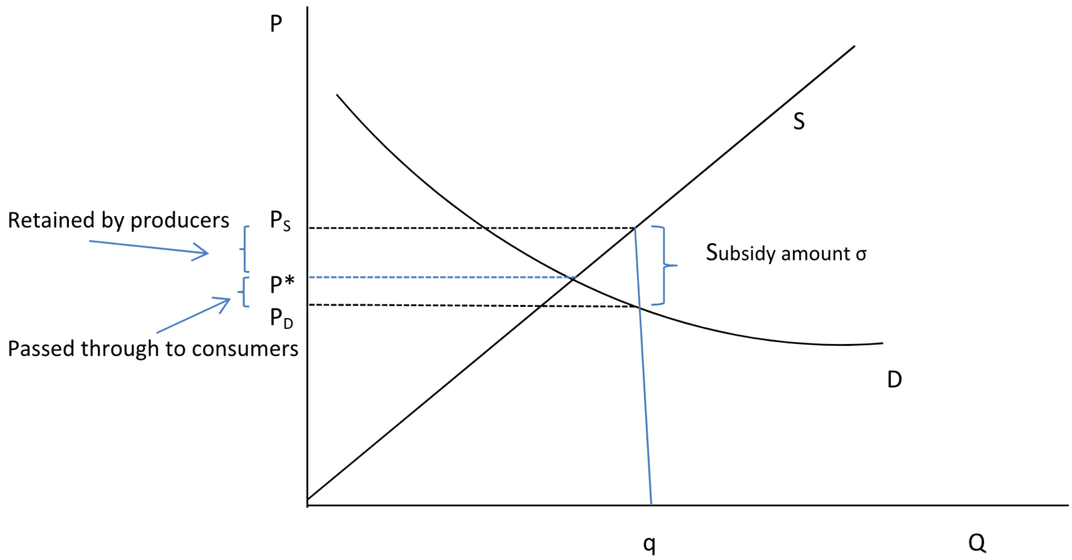
Specifically, in the counterfactual scenario (i) *No EV policies*, I remove both the EV subsidy and the GLP policy and keeping no EV policies in effect by removing the EV license plate choice in Stage 1 and set the subsidy amount d_{mt} in equation (5) to be 0.

In the counterfactual scenario (ii) *only EV subsidies*, I keep only the EV subsidy and remove the GLP policy by eliminating the choice of EV license plate in Stage 1 in the simulation process.

In the counterfactual scenario (iii) *only the GLP policy*, I keep only the GLP policy and remove the subsidy policy by setting the subsidy amount in equation (5) to 0.

F Subsidy Pass-Through

Figure 9: Subsidies in Competitive Markets



G Empirical Analysis of License Quota Policy

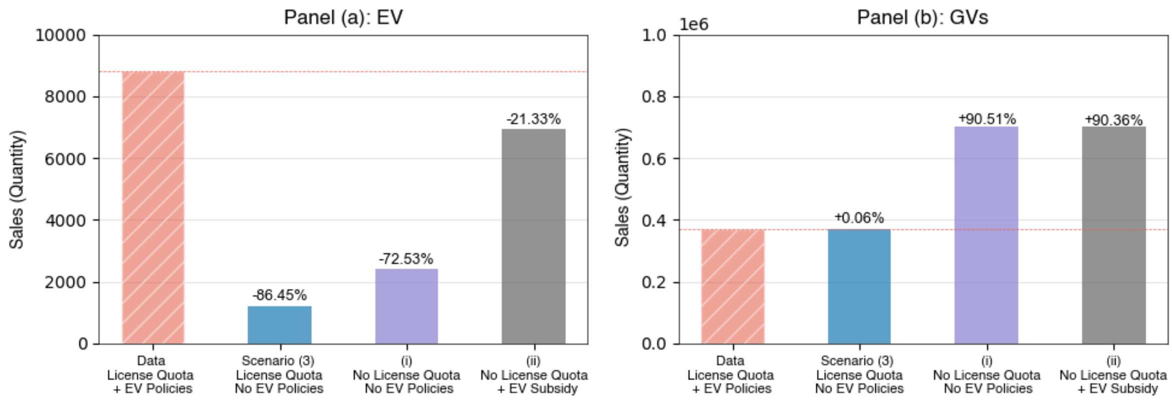
So far, I've demonstrated the impacts of EV subsidy and the GLP policy in deploying EVs and evaluated the net welfare gains led by both policies. Nonetheless, for economies having not adopted the license quota policy, our analysis is not enough to provide policy implications as the license quota policy 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.

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 this study, I simulate two counterfactual scenarios in the context of Beijing, 2015: (i) *the null case*, assuming tht all the three policies: the license quota policy, the GLP policy and the EV subsidy were removed; and (ii) *the null case but keep the EV subsidies*, where only the license quota policy and the GLP policy were removed.

Figure 10 presents the simulation results. If the license quota policy had been removed, total annual GV sales in Beijing would have increased by 90.51%, indicating that the license quota policy was effective in curbing vehicle consumption. Additionally, I find that annual EV sales would have decreased by 72.53% in the absence of the license quota policy as well as the two primary EV adoption policies. If the government had not implemented the license quota policy but provided EV subsidies, annual EV sales would have decreased by 21.33%.

Figure 10: 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 GLP 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 GLP policy) based on consumers surplus, producer surplus, government expenditures and externalities associated with vehicle usage following the empirical method introduced in Section 6.4. This policy analysis offers insights on the adoption of license quota together with EV subsidy and the green license policy in the automobile market.

Table 8 displays the total welfare comparisons of license quota policy along with EV subsidies and the GLP policy. It shows that simply adopting the license quota policy would decrease the total number of GVs on the road by 47.5% (calculated as $\frac{(368{,}600-701{,}787)}{701{,}787}$), and thus efficiently reduces the environmental externalities led by vehicle usage by around \$6.801 millions - \$9.542 millions (calculated as 14.325-7.524, and 20.097-10.555, respectively) based on the estimates for annual external cost.

As for the net welfare impact of the license quota policy, I find that the net welfare surplus of the license quota policy depends largely on the assumption of annual external cost estimates. For example, given the mean estimates for external costs, the adoption of the license quota policy could lead to a net welfare loss compared to the scenario with no license quota policy due to the deadweight loss. However, if the environmental externalities are expected to be high, then the implementation of the license quota policy would lead to a positive net welfare surplus as the environmental externality gains exceed the deadweight loss. This provides important policy implications for economies facing similar environmental problems (congestion, pollution) as Beijing.

Conditional on the implementation of a license quota policy, I find that the adoption of EV subsidies and the GLP policy could lead to additional net welfare gains relative to the null case, as shown in Table 8. This indicates that it is more efficient to adopt the GLP policy and EV subsidies if the license quota policy has been implemented in terms of overall net welfare surplus in the auto market.

Note that my analysis of the license quota policy is based on the lottery allocation system in Beijing. According to Li (2018) and Guo and Xiao (2022), an auction license allocation system, which could increase government revenue, could potentially make the license quota policy substantially more efficient.

As a point of reference, the average bid price for a license plate was around \$13,575 in Shanghai in 2015. Holding all other factors constant, adopting the clearing price of \$13,575 per license plate in an auction system to allocate the license plates in Beijing could generate an additional \$1.47 billion in government revenue from around 105,600 license quotas. This additional revenue would even outweigh the net deadweight loss (1.518-0.798) due to quota constraints, implying that there could be a larger net welfare surplus by adopting the license quota policy with an auction system.

Overall, my 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.

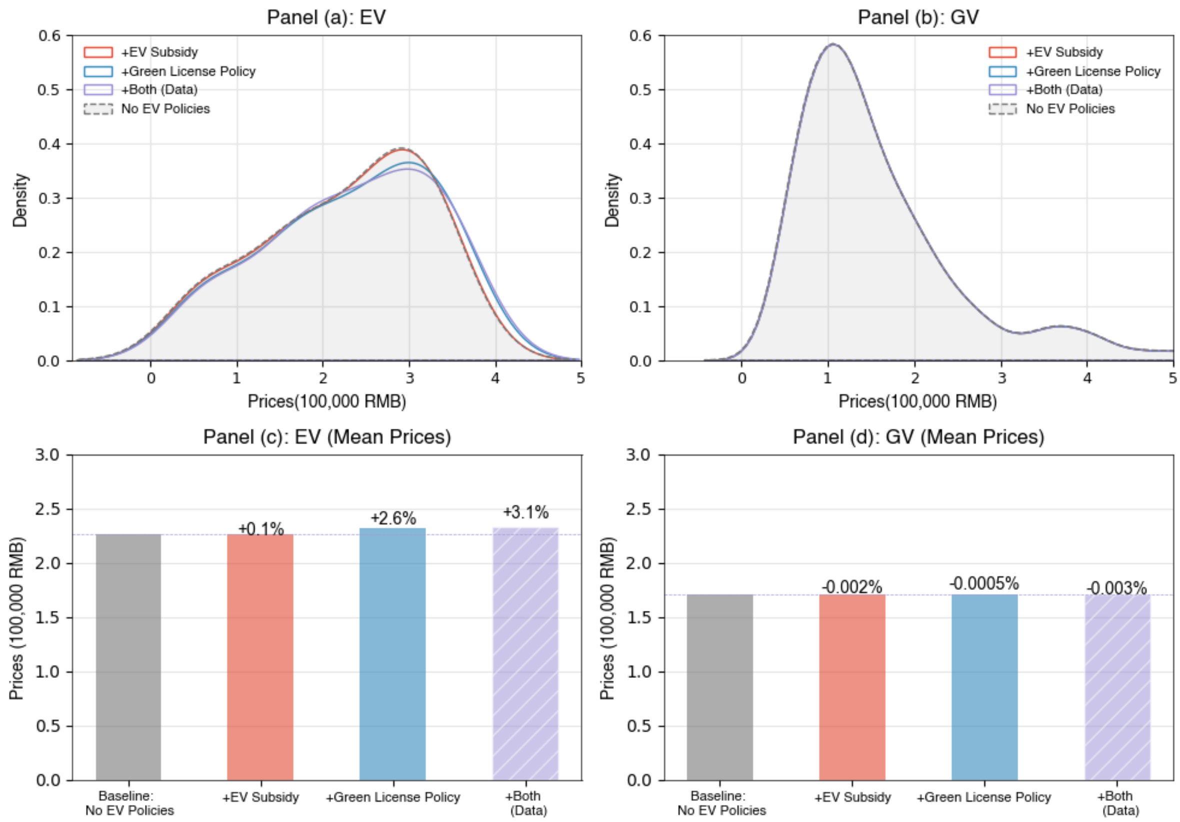
Table 8: Welfare Results

	(Null)	(i)	(ii)	(iii)	(iv)
License Quota Policy (lottery)	No	YES	YES	YES	YES
EV Policies	No	*No EV Policies*	*Only EV Subsidy*	*Only GLP Policy*	*Both*
Regular License Quotas	-	105,600	105,600	105,600	105,600
EV License Quotas	-	-	-	20,000	20,000
EVs Deployed	2,418	1,193	3,367	3,658	8,804
GVs	701,787	368,600	368,215	368,622	368,373
Welfare **$ in billion**	Absolute Values				
Consumer Surplus (CS)	12.139	6.357	6.394	6.399	6.487
Producer Surplus (PS)	3.704	1.965	1.975	1.985	2.027
EV Producers	0.013	0.006	0.019	0.027	0.070
GV Producers	3.692	1.959	1.956	1.959	1.957
Government Expenditure (GExp)	0	0	0.024	0	0.064
CS + PS - GExp	15.844	8.322	8.346	8.384	8.450
Externalities (EC, mean)	-14.325	-7.524	-7.522	-7.531	-7.540
Net Welfare Surplus (mean)	1.518	0.798	0.824	0.853	0.911
Net Welfare Surplus Changes (%)	-	-47.4%	-45.7%	-43.8%	-40.0%
Externalities (EC, max)	-20.097	-10.555	-10.551	-10.564	-10.574
Net Welfare Surplus (min)	-4.253	-2.233	-2.206	-2.180	-2.123
Net Welfare Surplus Changes (%)		+47.5%	+48.1%	+48.7%	+50.1%

***Notes**: The table shows the total welfare outcomes of the four counterfactual scenarios and the data case during the sample data period (Beijing, 2015). Welfare changes are measured in billions of dollars per year. I present the mean and upper bound of total environmental externalities due to reduced vehicle usage, based on with the mean and upper bound of YEC (annual external cost per vehicle per VMT) with a minimum estimate for vehicle lifetime of 7 years.*

H Impacts of EV Subsidy and the GLP Policy on Prices

Figure 11: 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 prices of EVs and GVs in the four scenarios. Panel (c) and (d) present price 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 baseline scenario.*

I EV Whitelist

Beyond EV subsidies and the green license plate policy, Beijing's approach to promoting electric vehicles includes a less conspicuous, protective practice known as the whitelist policy. The Beijing government published its whitelist[1] of eligible electric vehicles (EVs) to

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

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

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.[2] (Barwick, Cao and Li, 2021).

In this study, my 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.[3]

To assess the impacts of the whitelist policy on market outcomes, 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 (ii) where I remove the subsidy

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

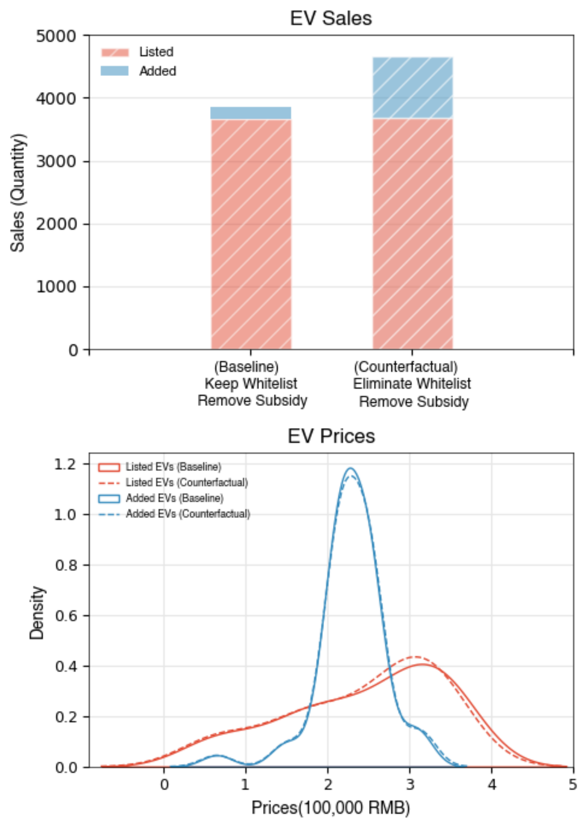
[2] Referenced from a report by the China Association of Automobile Manufacturers

[3] 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.

but keep the GLP policy with the whitelist as the baseline scenario.

Figure 12 presents the counterfactual sales and prices of EVs in the scenario without the whitelist compared to the baseline scenario. The equilibrium impacts on GVs are not displayed as they are minimal. As shown in Figure 12, eliminating the whitelist could lead to a significant increase in the sales of EVs originally not on the list, while having almost no effect on the sales of EVs on the list. This implies that eliminating the whitelist would be a beneficial practice to promote the diffusion of EVs not on the list. Additionally, the prices of EVs originally on the list would have decreased slightly if the whitelist had been eliminated, suggesting that eliminating the whitelist could benefit consumers by reducing the prices of EVs on the list.

Figure 12: Counterfactual EV Market Outcomes



***Notes**: The figure plots the equilibrium sales and prices in the baseline scenario and the counterfactual scenario where I eliminate the whitelist in the context of Beijing, 2015. In the figure, the legend listed EVs denotes those EV products that were originally on the whitelist, and added EVs refers to those included in the counterfactual analysis. The upper panel represents the total sales of listed EVs and added EVs, while the lower panel displays the price distribution of listed EVs and added EVs.*