



# A Game-Theory Analysis of Electric Vehicle Adoption in Beijing under License Plate Control Policy

Lijing Zhu, Jingzhou Wang, Arash Farnoosh, Xunzhang Pan

## ► To cite this version:

Lijing Zhu, Jingzhou Wang, Arash Farnoosh, Xunzhang Pan. A Game-Theory Analysis of Electric Vehicle Adoption in Beijing under License Plate Control Policy. *Energy*, 2022, 244 (Part A), pp.122628. 10.1016/j.energy.2021.122628 . hal-03686100

**HAL Id: hal-03686100**

**<https://ifp.hal.science/hal-03686100>**

Submitted on 2 Jun 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# **A game-theory analysis of electric vehicle adoption in Beijing under license plate control policy**

**Lijing Zhu<sup>1</sup>, Jingzhou Wang<sup>1,2</sup>, Arash FARNOOSH<sup>2</sup>, Xunzhang Pan<sup>1</sup>**

**1 School of Economics and Management, China University of Petroleum- Beijing, China**

**2 IFP Energies Nouvelles (IFPEN), IFP School, Rueil-Malmaison, France**

## **ABSTRACT**

To mitigate traffic congestion and to improve environment condition, license plate control(LPC) policy has been implemented in Beijing since 2011. For instance, almost 100,000 vehicle license plates were distributed in 2019, including 60,000 electric vehicle (EV) license plates and 40,000 gasoline vehicle (GV) license plates. However, whether the current license plates allocation is optimal from a social welfare maximization perspective or not is an important question. In order to answer such a question, this paper aims to quantify the optimal EV license plates under the LPC policy in Beijing. A two-level Stackelberg game is proposed so as to portray the interaction between vehicle applicants and the government. The equilibrium EV license plate allocation and market share are derived from the Stackelberg model. After optimization, the number of EV license plates is 58800 and its market share could be improved by 15%. Sensitivity analysis is conducted to better illustrate the impact of certain influential factors such as license plate quota, energy prices, and vehicle rental fee on EV adoption. The results indicate that increment in total license plate quota contributes to EV

penetration. For Beijing government, in particular, assigning license plates to EV applicants exclusively is much effective in promoting EV diffusion. Considering a 33% increment in current EV license plates allocation level, EV market share could expand by 10.5%. In terms of energy prices, when gasoline price is low, reducing electricity price would contribute to EV promotion significantly, while that effect fades as the gasoline price rises. Apart from it, influence caused by vehicle rental fee on EV penetration is also explored, which shows that lower rental fee is conducive to EV penetration. Therefore, incentives to mitigate rental fee should be considered by the policy-makers.

**Keywords:** Electric vehicle, License plate control (LPC) policy, Stackelberg game theory, EV Market share

#### Abbreviation

LPC policy	license plate control policy
EV	electric vehicle
GV	gasoline vehicle
$P_G$	the average price of gasoline vehicle
$P_E$	the average price of electric vehicle
$I_G$	the number of fuel charging stations in Beijing
$I_E$	the number of charging piles in Beijing
$M_G$	the probability of undergoing tail number restriction in weekdays
$N_G$	the quantity of gasoline vehicle license plates
$B_G$	the number of gasoline vehicle applicants
$B_E$	the number of electric vehicle applicants
$K$	the total license plate quota
$P_{GV}$	the probability of purchasing gasoline vehicle
$P_{EV}$	the probability of purchasing electric vehicle

$\varepsilon_G$	the applicant's random preference for gasoline vehicles, uniformly distributed with $\varepsilon_G \sim u(0,1)$
$\varepsilon_E$	the applicant's random preference for electric vehicles, uniformly distributed with $\varepsilon_E = 1 - \varepsilon_G$
$\eta$	the market share of gasoline vehicle
$U_G$	the utility of gasoline vehicle applicant
$U_E$	the utility of electric vehicle applicant
$T_G$	the time of winning a gasoline vehicle license plate within lottery system
$T_E$	the time of obtaining an electric vehicle license plate within queuing up system
$c$	the rental fee per month
$DVKT$	Daily Vehicle Kilometers Travelled
$p$	the probability of winning a gasoline vehicle license plate in one lottery
$P_g$	the price of gasoline
$P_e$	the price of electricity

## 1. Introduction

Beijing has undergone deteriorating traffic congestion and air pollution for a long time. In these years, replacing GVs with EVs becomes more and more prevalent within transportation sector (Yuan et al., 2015). Plenty of policies have been implemented to improve EV penetration, which are categorized as demand-based policies and supply-based policies (Zhuge et al., 2020). This paper will mainly focus on the demand-based policies which could be further classified as economic and non-economic policies. Actually, certain economic incentives had been carried out by Beijing government, such as GV purchasing tax increment in 2004, public transportation fare reduction in 2007, subsidies for EVs and infrastructures since 2011, and EV purchasing tax exemption in 2014. There is no doubt

that in the short term, the economic incentives are able to increase EV competitiveness more or less. However, the economic incentives mainly aim to promote EV adoption but cannot effectively limit vehicle quantity. In other words, economic incentives alone are insufficient to mitigate traffic congestion in Chinese metropolitans such as Beijing, Shanghai, and Guangzhou. Worse still, the economic incentives would increase financial burden of the government in the long run (Zhuge et al., 2020).

Alternatively, non-economic incentives, (license plate control (LPC) policy in particular), should be adopted by the policy-makers. Basically, LPC policy places a cap on the total quantity of new license plates each year. In addition, those license plates would be further allocated between EV and GV applicants respectively. Annual license plates allocation results of Beijing during recent years are shown in Fig.1. On the basis of this policy, Beijing government employs a queuing up system in order to distribute purchasing permits to EV applicants directly, whereas the GV applicants need to compete for the annual permits within a lottery system organized on 26th every two months by Beijing Municipal Commission of Transport. Each lottery winner receives a nontransferable certification to purchase a vehicle (Yang et al., 2014).

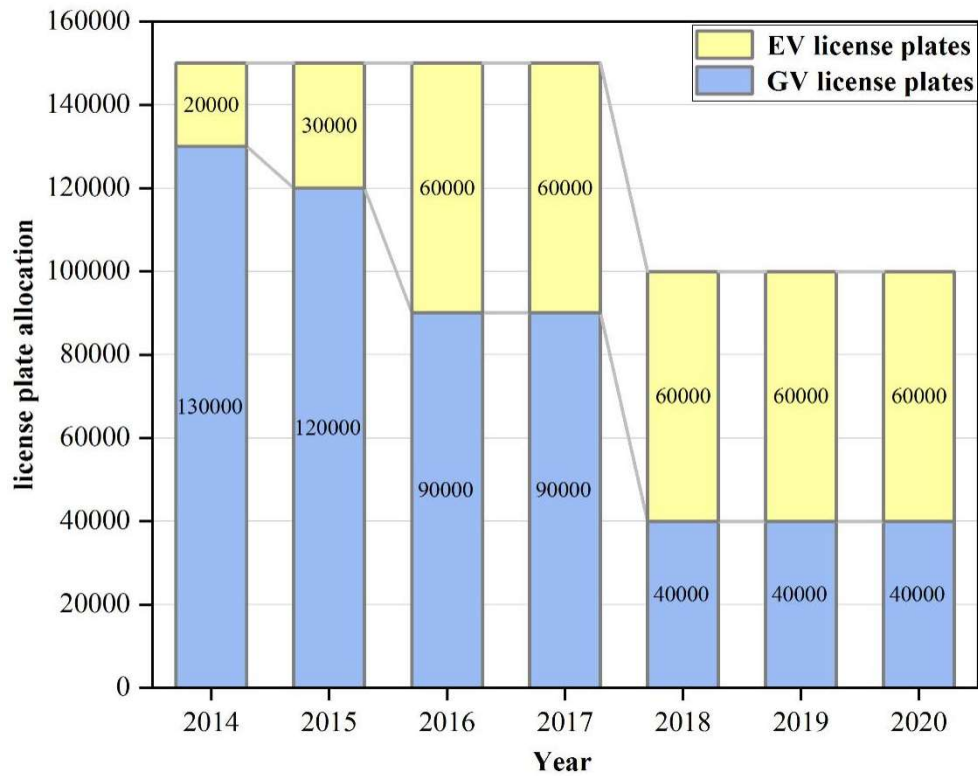


Fig. 1. Results of license plate allocation in Beijing from 2014 to 2020

Source: calculated by the authors according to The People's Government of Beijing Municipality

In 2019, over 3350500 GV applicants registered on the website, according to the statistical result of The People's Government of Beijing Municipality <sup>1</sup>, while the annual quota of GV license plate was 40000. Probability of winning a GV license plate is 0.2% approximately, which implies that individual applicant needs to spend almost 41 years winning a GV license plate. However, it would take each EV consumer about 9 years to obtain a EV license plate within the queuing up system. Some applicants tend to choose EVs so that they can get vehicles as soon as possible, which would improve EV adoption significantly. License plate allocation result influences the purchasing decision of applicants, which further impacts the social utility with respect to consumer utility and environment impact. Nevertheless, given an annual aggregate quota, how to allocate license plates between EVs and GVs in

<sup>1</sup> The People's Government of Beijing Municipality: Official website of the Beijing government which offers information on living in Beijing as well as other practical information.

order to maximize social utility has not been analyzed among the current studies.

This paper plans to identify the optimal license plate allocation between EVs and GVs. Main contributions of this study are: First, optimal license plate distribution of EVs and GVs under Beijing's LPC policy is identified. Second, the influence of license plate distribution on EV promotion is analyzed. Third, the impact of certain influential factors on EV penetration are discussed, in addition, corresponding implications are provided to the policy-makers.

The rest of paper is organized as follows: In section 2, the related literature is reviewed. In section 3, we propose a Stackelberg model between the government and applicants and prove the existence of equilibrium results. In section 4, the practical equilibrium results are obtained by applying actual value of parameters. In section 5, we discuss the results and provide implications in order to improve EV adoption.

## **2. Literature review**

### **2.1 Policies for improving EV adoption**

Various of policies have been implemented so far to improve EV penetration. (Zhang, 2014);(Yang et al., 2014);(Helveston et al., 2015);(Zhu et al., 2019). Among them, subsidy is the most widely-discussed economic incentive. (Jenn et al., 2018) proposed three distinct generalized models so as to evaluate the effect of economic incentives on EV adoption and demonstrated that every \$1000 rebate would promote the sales of EV by 2.6%. Similarly, using a large random sample of individual, (Sheldon et al., 2020) demonstrated that if the subsidy were reduced by 50% due to the phasing out subsidy policy in China, the EV market share would have declined by 21%.

Although subsidy has been regarded as an effective approach to improve EV diffusion, certain flaws cannot be ignored either: Firstly, subsidy policy could only increase the competitiveness of EV in a short run. In the long run, as EV adopters increase, government tends to reduce the scale of subsidy to alleviate financial burden, which weakens the EV competitiveness consequently (Zhuge et al., 2020). For instance, (Ma et al., 2017) illustrated that technology was a bottleneck factor for EV adoption and technology progress was much more influential than subsidy. (Jang et al., 2018) claimed that policy treating EV and GV vehicle technologies in a fair manner might be better than consumer-oriented subsidy policy. Secondly, implementation of subsidy policy is comparatively complicated. Once the incentive policy was conducted improperly, it would interrupt the vehicle market or even cause a backfire to it (Gneezy et al., 2011). Having witnessed the fluctuation of Sweden EV market in 2014 that EV market share in Sweden declined from 2.1% in August to less than 1.0% in November because of the rebate shortage, (Tietge, 2017) implied that subsidy might result in unexpected damage to the EV improvement under extreme circumstance.

By contrast, as a typical non-economic policy, LPC policy will be mainly discussed in this study. After the first LPC policy was implemented in Shanghai in 1994, Beijing proposed a unique LPC policy which simultaneously regulated the license plate allocation of EVs and GVs by lottery systems (Wang et al., 2017) in 2010. Specifically, given fixed quantity of EV and GV license plates, applicants who would like to purchase EVs or GVs have to attend separate lottery systems in order to achieve license plates. However, to stimulate EV adoption, Beijing government has cancelled the lottery mechanism during EV application and required EV applicants to queue up for obtaining EV license plates, since October 2015. However, those who plan to purchase GV still have to enter a lottery

system and compete for the purchase certificate (Zhang et al., 2018).

Generally, LPC policy includes auction and lottery (Yang et al., 2014);(Zhang et al., 2018);(Zhuge et al., 2020). Two reasons that lottery mechanism is preferred by Beijing government are illustrated by (Yang et al., 2014): Firstly, compared with the auction in Singapore for the first time and followed by Shanghai in 1994 (Chen and Zhao, 2013);(Yang et al., 2014), lottery mechanism is more fair for all citizens. Without any special requirement, applicants can register on the government website for free. Secondly, having distributed the residential houses with a lottery system successfully, Beijing government is expected to apply a similar lottery system in vehicle market successfully. So far, many studies are focusing on the lottery mechanism implemented in Beijing. (Yang et al., 2014) analyzed the short term effect of lottery policy on Beijing's traffic situation and found that the congestion has been mitigated significantly because of the lottery policy. In more details, they (Yang et al., 2020) estimated that lottery mechanism could reduce the daily vehicle kilometers travelled and the usage of cars in rush hour by 15% and 10% respectively. By conducting survey on 332 respondents, (Zhang et al., 2018) assessed the influence of lottery policy on EV adoption and suggested that lottery policy was more suitable and powerful to promote EV penetration in Beijing. (Zhuge et al., 2020) proposed an agent-based model and asserted that not only did the lottery policy in Beijing influence the EV adoption significantly, but it also reduced the energy consumption and emission of vehicle.

Furthermore, due to Beijing's allocation mechanism that each vehicle consumer needs to attend the lottery system or queuing up system so as to obtain a GV or EV license plate, applicants are more sensitive to the specific allocation regulated by the government which influences their utility directly. However, research focusing on this influential factor is still insufficient among current literature.

## 2.2 Models for evaluating EV incentives

Methodologies have been widely utilized within current studies to evaluate the effectiveness of EV incentives, such as discrete choice model (Wang et al., 2017), regression model (Clinton et al., 2015);(Mersky et al., 2016), agent-based model (Silvia et al., 2016);(Zhuge et al., 2020), multi-layer perspective model (Djalante et al., 2012);(Figenbaum, 2017), and game theory model (Qin et al., 2015);(Jang et al., 2018);(Zhu et al., 2019). A discrete choice model involving 247 respondents was employed by (Wang et al., 2017) to compare the effectiveness of several policies. The result showed that LPC policies implemented in certain Chinese cities had significantly positive impact on EV penetration. By developing a multiple linear regression, (Wang et al., 2019) found that direct subsidy scheme could not account for the different EV penetration levels among countries. (Silvia et al., 2016) established an agent-based model which simulates and compares four distinct policies with the benchmark. Likewise, (Zhuge et al., 2020) proposed an agent-based spatial integrated model named SelfSim-EV then investigated how incentives impacted individual purchasing behaviors. The result suggested that purchasing permit policy could significantly influence on EV penetration.

Stackelberg game model is frequently applied to model the hierarchical interaction among stakeholders with distinct objectives (Zhu et al., 2017);(Qin et al., 2015);(Yu et al., 2016);(Jang et al., 2018). In order to improve the effect of government interference on vehicle market, a trilateral game model incorporating the government, vehicle manufactures, and vehicle applicants was employed by (Qin et al., 2015) . A sequential game was introduced by (Yu et al., 2016) to model the interaction between charging infrastructure investors and EV consumers. (Zhu et al., 2017) proposed a three-level Stackelberg game portraying the interaction among electricity supplier, charging infrastructure

operator, and crowd-funders. Besides, a stylized Stackelberg game among vehicle manufacturers, applicants, and energy suppliers was depicted by (Jang et al., 2018) so as to identify policy implications for improving EV diffusion.

In this paper, we consider two players involved within the license plates allocation system under LPC policy: the government and vehicle applicants. The government regulates vehicle license plate allocation, then applicants decide to purchase EVs or GVs. Given this hierarchical interaction, a two-level Stackelberg game model is proposed in this paper so as to quantify EV license plate distribution and to explore influential factors and their impact on EV adoption.

### **3. Methodology**

#### **3.1 Structure of Stackelberg game model**

We consider that there are two players in the vehicle market under the LPC policy: the government and vehicle applicants. The government regulates specific license plate distribution between EV and GV then carries it out. Given fixed distribution, each consumer needs to consider whether purchasing EV or GV to maximize his/her own utility. For analytical tractability, we assume that vehicle applicants are homogenous and rational. The interaction between these two participants is portrayed in the diagram below.

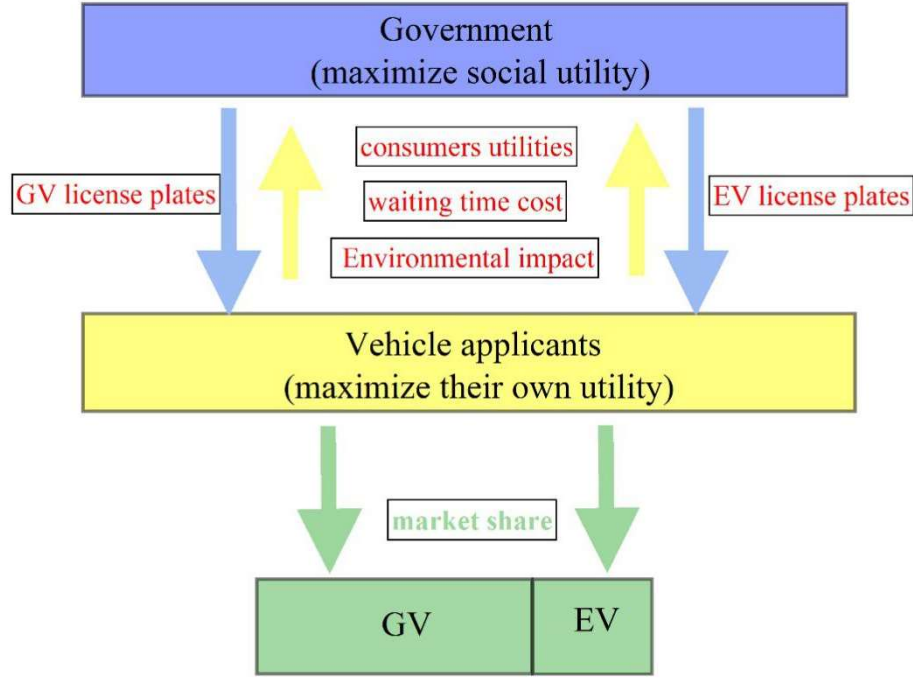


Fig.2. Interaction between the government and vehicle applicants

Stackelberg game model is applied to depict the interaction between the government and vehicle applicants. Commonly, a Stackelberg game framework is established to depict the hierarchical interaction among participants, where a leader has sufficient power over followers. Within the game framework, a strategy is determined by leader firstly to maximize its utility and the followers react sequentially based on the leader's strategy (Zhang et al., 2017). In this case, the government could be regarded as leader, while the applicants act as followers. The optimal license plate distribution obtained within this system depends on each participant's behavior: As for the vehicle applicants, the allocation between EV and GV license plates regulated by the government influences their utility directly, impelling them to choose between EVs and GVs. Reversely, aggregate applicants' utilities, waiting time cost, and environmental impact caused by the applicants' purchasing choices contribute to the social welfare. In other words, they influence the government's decision process.

### 3.2 Decision model of consumer

Discrete choice models have been used widely to model the vehicle purchasing decisions of applicants. In this study, the model is applied to calculate the probability of choosing a specific type of vehicle under certain attributes. Commonly, attributes including individual consumer's characteristics (He et al., 2018);(Ouyang et al., 2018);(Chu et al., 2019), government incentives (Diamond, 2009);(Lin et al., 2018), and charging or refueling infrastructures (Javid et al., 2017);(Egnér et al., 2018) are considered to influence purchaser's behavior significantly. Correspondingly, the utility functions shown in Eqs. (1) and (2) are formulated as the weighted sum of attributes incorporating vehicle prices, number of charging/refueling stations, car tail number restriction, and possibility of obtaining a license plate.

$$U_{GV} = \beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + \beta_4 * N_G / (6 * B_G) + \varepsilon_G \quad (1)$$

$$U_{EV} = \beta_1 * P_E + \beta_2 * I_E + \beta_4 * (K - N_G) / B_E + \varepsilon_E \quad (2)$$

Where  $P_G, P_E$  are the average prices of GV and EV respectively;  $I_G, I_E$  refer to the number of fuel charging stations as well as charging piles in Beijing;  $M_G$  measures the probability of undergoing tail number restriction in weekdays for each gasoline vehicle;  $N_G$  represents the quantity of GV license plates;  $B_E$  denotes the number of applicants who are willing to purchase EVs, whereas  $B_G$  denotes the number of those tending to purchase GVs;  $K$  is the total license plate quota issued by Beijing government.

$\beta_1, \beta_2, \beta_3$ , and  $\beta_4$  are parameters describing consumer's sensitivities towards certain influential factors.  $\beta_1$  measures consumer's sensitivity towards vehicle prices;  $\beta_2$  measures the sensitivity

towards infrastructure quantity;  $\beta_3$  measures the sensitivity towards possibility of undergoing tail number restriction;  $\beta_4$  refers to the sensitivity towards the probability of obtaining a license plate. On the basis of binary logit model, the possibility that individual applicant chooses whether EV or GV could be respectively defined as:

$$P_{EV} = \frac{e^{U_{EV}}}{e^{U_{EV}} + e^{U_{GV}}} \quad (3)$$

$$P_{GV} = \frac{e^{U_{GV}}}{e^{U_{EV}} + e^{U_{GV}}} \quad (4)$$

Where  $P_{EV} + P_{GV} = 1$ . After combining and modifying of Eqs. (3) and (4), a new regression equation is established as:

$$\ln(P_{EV}/(1 - P_{EV})) = \beta_1 * (P_E - P_G) + \beta_2 * (I_E - I_G) - \beta_3 * M_G + \beta_4 * ((K - N_G)/B_E - N_G/(6 * B_G)) \quad (5)$$

To estimate the values of four parameters, a survey is introduced in this paper. The survey is implemented on Wenjuanxing, an online crowdsourcing platform in China mainland, from March to May in 2020. Each respondent is required to complete a questionnaire during the survey. In more detail, the questionnaire comprises two parts: the demographic information in the first part involves gender, age, education level, household income, and family number. The second part measures the respondent's sensitivities towards various factors which include vehicle prices, infrastructure quantity, possibility of undergoing tail number restriction, and probability of obtaining a license plate.

Totally, 125 questionnaires were collected in this study and 23 questionnaires were invalid because of the missing data. The sample's demographic data is shown in Table 1.

	Frequency	Percentage(%)
<b>Gender</b>		
Male	53	51.96
Female	49	48.04
Total	102	100

<b>Age</b>		
25 and below	19	18.63
26-35	52	50.98
36-45	21	20.59
46-55	8	7.84
56 and above	2	1.96
Total	102	100
<b>Educational level</b>		
Middle school degree and below	4	3.77
High middle school degree	8	7.55
Bachelor's or associate degree	50	49.06
Master's degree	28	28.30
Doctor's degree	12	11.32
Total	102	100
<b>Family member</b>		
1	8	7.55
2	23	22.64
3	35	33.96
4	17	16.98
5 and above	19	18.87
Total	102	100
<b>Household Income (CNY; Month)</b>		
10000 and below	25	24.53
10001-20000	38	37.74
20001-30000	21	20.75
30001-40000	6	5.66
40001 and above	12	11.32
Total	102	100

Table.1. The demographic data of sample

Then a binary logistic model is implemented so as to measure the sensitive coefficients. On the basis of Eq. (5), we record the respondent who chose to purchase EV as 1, whereas the one who chose to purchase GV as 0. By inserting the data of 102 samples into the regression model, the results are derived and depicted in Table.2.

	$\beta$	Sig.
Vehicle price	-0.32	0.051
Infrastructure quantity	0.13	0.011
Probability of undergoing tail number restriction	-0.11	0.22
Probability of obtaining a license plate	0.44	0.00
Constant	-1.295	0.42
-2 Log likelihood	64.073	

Cox & Snell R <sup>2</sup>	0.505
Nagelkerke's R <sup>2</sup>	0.686
Overall percentage correct	84.30%

Tabel.2. The results of logistic regression

As it is shown in Table. 2, four sensitive coefficients ( $\beta_1, \beta_2, \beta_3$ , and  $\beta_4$ ) involved in the regression are estimated. Besides,  $\varepsilon_G$  and  $\varepsilon_E$  are random variables referring to the unquantified attributes of applicants. Based on the studies of (Yu et al., 2016) and (Zhu et al., 2019), we assume that the random variables are subjected to the uniform distribution  $u(0,1)$ . Both  $\varepsilon_G$  and  $\varepsilon_E$  vary from 0 to 1 and the relationship between random variables is:

$$\varepsilon_G + \varepsilon_E = 1 \quad (6)$$

To maximize their own utility, applicants need to decide which type of vehicle they would like to purchase. The expected individual utility could be expressed as:

$$U_{consumer} = \text{Max}(U_G, U_E) \quad (7)$$

Combine the upper formula with the relationship between  $\varepsilon_G$  and  $\varepsilon_E$  ( $\varepsilon_G + \varepsilon_E = 1$ ), the threshold of GV market share,  $\eta^*$ , can be deduced:

$$\eta^* = \frac{(\beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + 1 - \beta_1 * P_E - \beta_2 * I_E - \beta_4 * (K/B_E) + \beta_4 * (1/B_G + 1/B_E) * N_G)}{2} \quad (8)$$

**Proof. See Appendix A.**

So, consumer's decision could be:

when  $\eta < \eta^*$ ,  $U_{consumer} = \text{Max}(U_G, U_E) = U_G$ , consumer chooses GV;

when  $\eta > \eta^*$ ,  $U_{consumer} = \text{Max}(U_G, U_E) = U_E$ , consumer chooses EV;

The diagram below shows the mechanism of consumer purchase decision making:

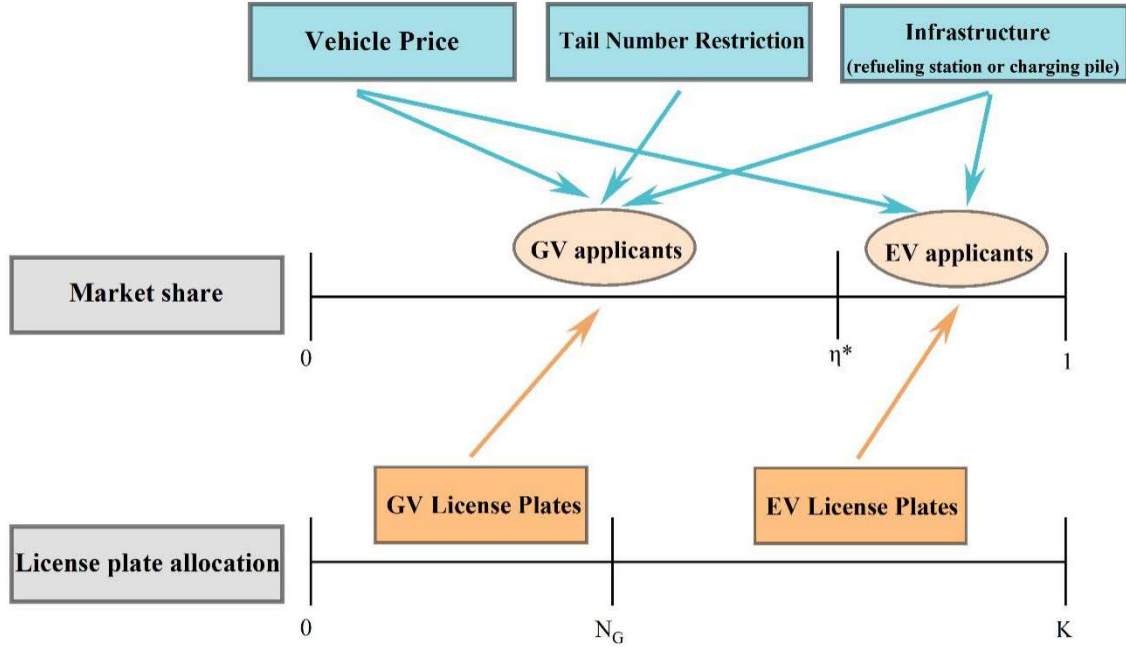


Figure.3. Diagram of the vehicle applicants' purchase decision

Consequently, the expected utility function for each consumer could be expressed as:

$$U_{consumer} = \int_0^{\eta^*} (\beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + \beta_4 * N_G / (6 * B_G) + \varepsilon_G) d\varepsilon_E + \int_{\eta^*}^1 (\beta_1 * P_E + \beta_2 * I_E + \beta_4 * (K - N_G) / B_E + \varepsilon_E) d\varepsilon_E \quad (9)$$

### 3.3 Waiting time cost

Waiting time cost is the expense of the applicants who are willing to purchase vehicles but actually do not achieve the license plates, due to the license plates control(LPC) policy. As the result of the limited quantities of EV and GV license plates, plenty of potential applicants cannot achieve their license plates in every year. We assume that so as to obtain similar commuting experiences, applicants tend to rent vehicles until they obtain license plates eventually. Total rental expense afforded by applicants during their waiting time is regarded as the implementary cost of LPC policy and impacts

social welfare inevitably. Consequently, as a significant factor, waiting time cost should be considered by the government when regulating license plate allocation.

Currently, the mechanisms of distributing EV and GV license plates in Beijing are totally different. GV license plates are allocated within a public lottery system, whereas queuing up system is applied for EV applicants. In the following part, the expected waiting time of EV and GV applicants are formulated respectively.

### 3.3.1 Expected waiting time of GV applicants

For GV applicants, the probability of winning a license plate definitely determines their waiting time. To calculate the waiting time of GV applicants, an innovative duration model proposed by (Hou et al., 2013) is employed in this paper. By incorporating the hazard function, this model identifies the relationship between the possibility of winning a GV license plate and the expected waiting time of GV applicants, which is depicted as below:

$$E(T_G) = [\int_0^{\infty} t * p * (1 - p)^t * e^{\left(p * \left[1 - \frac{(1-p)^t}{\ln(1-p)}\right]\right)} dt] / 6 \quad (10)$$

Where  $p^2$  is the possibility of winning a GV license plate. **Proof. See Appendix B.**

Based on this equation, we could simulate the expected waiting time of each GV applicant under different winning probability.

---

<sup>2</sup> Beijing government organizes 6 lotteries each year. Since  $N_G$  is the number of GV license plates to be distributed in this year, whereas the number of GV applicants is  $B_G$ , the probability of winning a GV license plate in one lottery,  $p$ , equals to  $\frac{N_G}{6 * B_G}$ .

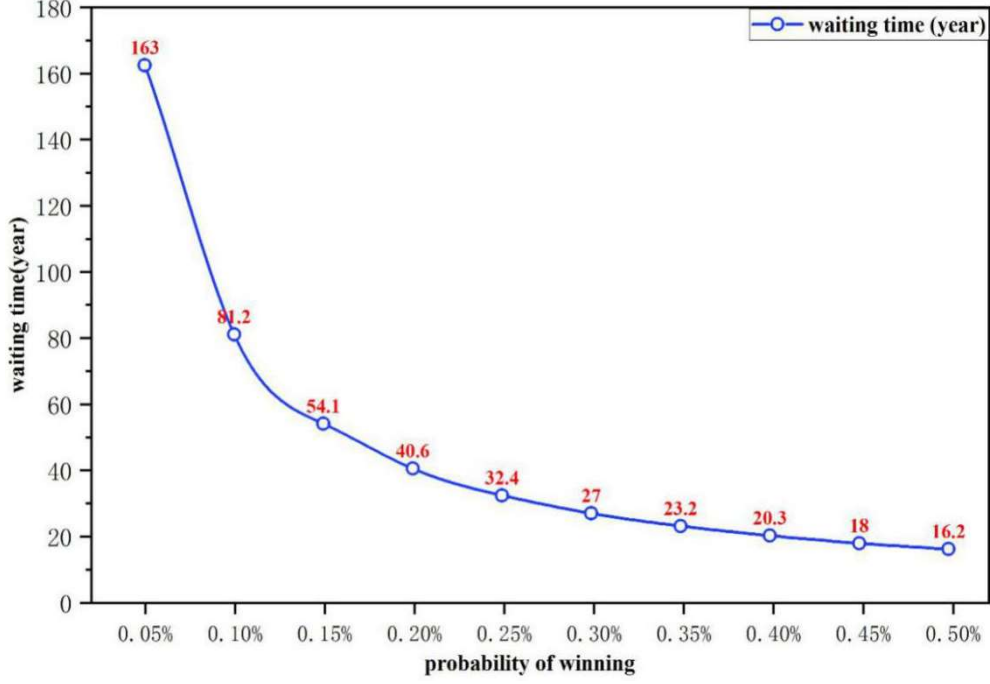


Figure.4. Waiting time of individual GV applicant under different winning probability levels.

In 2020, the quantity of GV license plates distributed is 40000, which means that the current possibility of winning a GV license plate is only 0.2%. By referring to Figure.4, we could predict that it would approximately take an individual 41 years to win a GV license plate under current winning probability.

### 3.3.2 Expected waiting time of EV applicants

Compared with the GV license plate lottery system, a queuing up system is applied to allocate EV license plates. Since we have known that the number of applicants within queuing up system is  $B_E$  and that the annual EV license plate quantity is  $(K - N_G)$ , we can deduce the expected waiting time for each candidate.

$$\mathbf{E}(T_E) = B_E / (K - N_G) \quad (11)$$

The aggregate waiting time cost can be calculated as below:

$$\{[\int_0^\infty t * p * (1 - p)^t * e^{(p * [1 - \frac{(1-p)^t}{\ln(1-p)}])} dt] / 6 + B_E / (K - N_G)\} * \frac{1}{2} * 12 * c * K \quad (12)$$

Where  $c$  is the vehicle rental fee per month

### 3.4 Environmental impact

Environmental impact stands for the influence on environment brought by the vehicles to be distributed within a given year. In fact, it is comparatively complicated to quantify the environmental impact of exhaust gas emitted by these vehicles directly. Under this circumstance, we calculate energy consumption cost as an alternative to indirectly portray environmental impact. To be specific, the cost of energy consumption refers to the expense paid by applicants for daily usage of gasoline and electricity during a given year. With respect to vehicle energy consumption levels, (Kong et al., 2012) has estimated that the average electricity consumption of EV is 17 kWh per 100 kilometers, whereas the average gasoline consumption level of GV is 8 liters per 100 kilometers. Consequently, considering that each year approximately has 360 days, annual energy consumption cost could be formulated as below:

$$[N_G * DVKT * 8/100 * P_g + (K - N_G) * DVKT * 17/100 * P_e] * 360 \quad (13)$$

Where  $DVKT^3$  is the average vehicle commuting distance in Beijing estimated by (Hou et al., 2013),  $P_g$  and  $P_e$  are gasoline price and electricity price.

### 3.5 Decision model of government

The government aims to maximize social welfare which includes the aggregate utility of vehicle

---

<sup>3</sup> As the abbreviation of “Daily Vehicle Kilometers Travelled”, DVKT measures the average commuting distance of vehicles in Beijing.

applicants, the waiting time cost of vehicle applicants caused by the LPC policy, and cost of energy consumed by EV and GV distributed in a given year. Among these three factors, aggregate utility of vehicle applicants is the gain of welfare, whereas the cost of waiting time and energy consumption are considered as the welfare loss. Correspondingly, social welfare function can be formulated as below:

$$\begin{aligned}
\pi_{social} &= \lambda_1 * (U_{applicants}) - \lambda_2 * (\text{waiting time cost}) - \lambda_3 * (\text{energy consumption cost}) \\
&= \lambda_1 * (\int_0^\eta (\beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + \beta_4 * N_G / (6 * B_G) + \varepsilon_G) d\varepsilon_E + \int_\eta^1 (\beta_1 * P_E + \beta_2 * I_E + \\
&\quad \beta_4 * (K - N_G) / B_E + \varepsilon_E) d\varepsilon_E) - \lambda_2 * (\int_0^\infty t * p * (1 - p)^t * e^{(p * [1 - \frac{(1-p)^t}{\ln(1-p)}])} dt) * \frac{1}{6} + \frac{B_E}{(K - N_G)} * \frac{1}{2} * 12 * c * \\
&\quad K) - \lambda_3 * (N_G * DVKT * 365 / 100 * 8 * P_g + (K - N_G) * DVKT * 365 / 100 * 17 * P_e) \quad (14)
\end{aligned}$$

Where coefficients  $\lambda_i$  ( $i=1, 2, 3$ ) are integrated into the welfare function in order to measure the gain and loss of the welfare.

### 3.6 Stackelberg equilibrium

Due to the complexity of Eq. (14), it is impractical to derive the closed form solution by solving the first and second derivatives. Under this circumstance, alternative approach should be adopted to prove the existence of the optimal value. Commonly, Mathematica<sup>4</sup> could be utilized to effectively provide information on the shape of a function, and in this case we introduce a frequently used graphics function, Plot<sup>5</sup>, which plots the graph of a function over a prescribed range of arguments. After inserting estimated values related to the parameters within Eq. (14), we manage to portray the social welfare over the range of independent variable  $N_G$  (where:  $0 < N_G < 100000$ ) in Fig. 5.

<sup>4</sup> As a sort of mathematical software application, Mathematica comprises thousands of powerful functions for numeric and graphical computation.

<sup>5</sup> The basic format of plotting is Plot [function, {variable, lower bound, upper bound}, Options]. In this paper, social welfare is the function we plan to depict,  $N_G$  serves as a variable, and the lower bound is 0, whereas the upper bound is  $K$  (100000 in benchmark level).

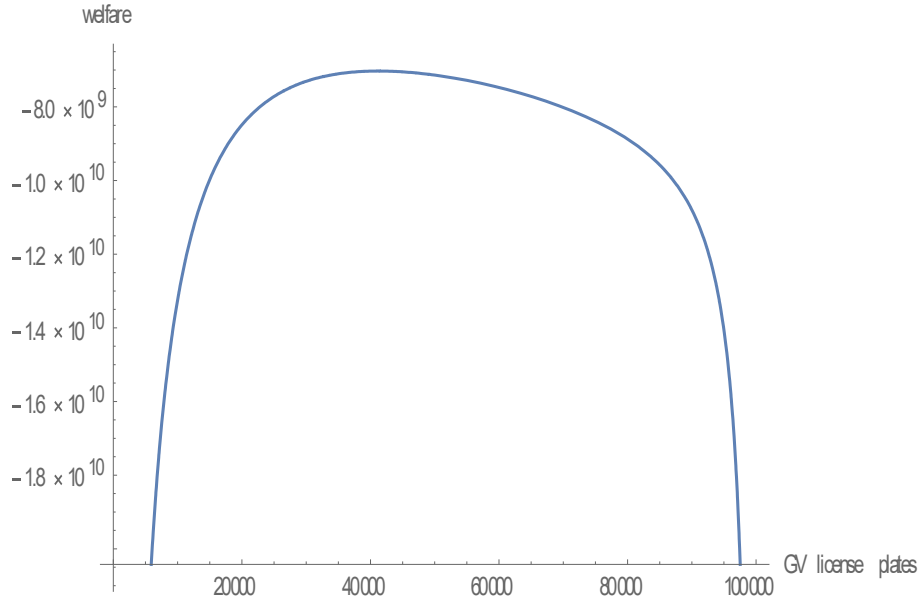


Figure.5. Social welfare over the range of GV license plate quantity

The concavity of the inverted U-shape in Figure. 5 indicates the existence of closed form solution ( $N_G^*$ ). Nevertheless, we could only obtain the approximate numerical solution. After substituting the approximate solution  $N_G^*$  into Eq. (8), we could derive the GV and EV market shares correspondingly.

#### 4. Estimation of parameters

Estimations of the key parameters incorporated this study are shown as below:

Parameter	Estimated value	Parameter	Estimated value
$\lambda 1$	1	$P_E$	$15 \times 10^4$
$\lambda 2$	0.046	$P_G$	$10 \times 10^4$
$\lambda 3$	10	$I_E$	$6.1 \times 10^4$
$\beta 1$	-0.32	$I_G$	$0.904 \times 10^4$
$\beta 2$	0.13	$M_G$	0.2
$\beta 3$	-0.11	$K$	100000
$\beta 4$	0.44	$P_e$	0.6
$B_E$	467400	$P_g$	5.31
$B_G$	3350500	$c$	2377
$DVKT$	46.35		

Table.3. The estimation of key parameters

According to the announcement of (The People's Government of Beijing Municipality, 2020), total license plates quota,  $K$ , has been 100000 since 2018. The number of applicants who are willing to purchase EVs,  $B_E$ , is 467400, whereas that of GVs,  $B_G$ , is 3350500. Besides, each GV in Beijing would be prohibited for one day in weekdays, which means that  $M_G$  equals to 0.2. The indexes of consumer's utility function are obtained from the regression model, where  $\beta_1 = -0.32$ ,  $\beta_2 = 0.13$ ,  $\beta_3 = -0.11$ ,  $\beta_4 = 0.44$ .

Approximately, the average price of electric vehicle  $P_E$  and gasoline vehicle  $P_G$  are 150000 CNY and 100000 CNY. According to the quotation of private cars in (Pacific Automotive Network, 2020). Moreover, the average cost of renting a vehicle,  $c$ , is estimated as 2377 CNY per month (Hou et al., 2013). Based on the statistical data derived from (China Electric Vehicle Charging Infrastructure Promotion Alliance, 2020), almost 61000 public charging piles have been installed in Beijing, implying that  $I_E$  equals to 61000, whereas there are 2260 gasoline stations in Beijing. We assume that each gasoline station is equipped with four refueling machines, which means that the aggregate quantity of refueling machines,  $I_G$ , is 9040. Furthermore, derived from the statistical data of (The State Council of the People's Republic Of China, 2020), the average electricity price  $P_e$  and gasoline price  $P_g$  are 0.6 CNY per kWh and 5.31 CNY per liter, respectively.

## 5. Result analysis and implication discussions

After applying the practical values of parameters into the Eq. (14), we can derive the equilibrium results: The optimal GV license plates quantity,  $N_G$ , is 41200, whereas the optimal EV license plates quantity is 58800. The market share of GV is 92.4%, while that of EV is 7.6%.

To provide managerial insights for policy makers, some influential factors and their effects on

vehicle market are discussed in this part.

### 5.1 The impact of the total quota on EV diffusion

From 2014 to 2018, the annual aggregate quota of license plates was 150000. However, since 2018, it has reduced from 150000 to 100000 according to the emission reduction need appealed by the central government, accounting for the difference in license plates results in recent years. Therefore, it is necessary to analyze the impact of the total quota on EV diffusion.

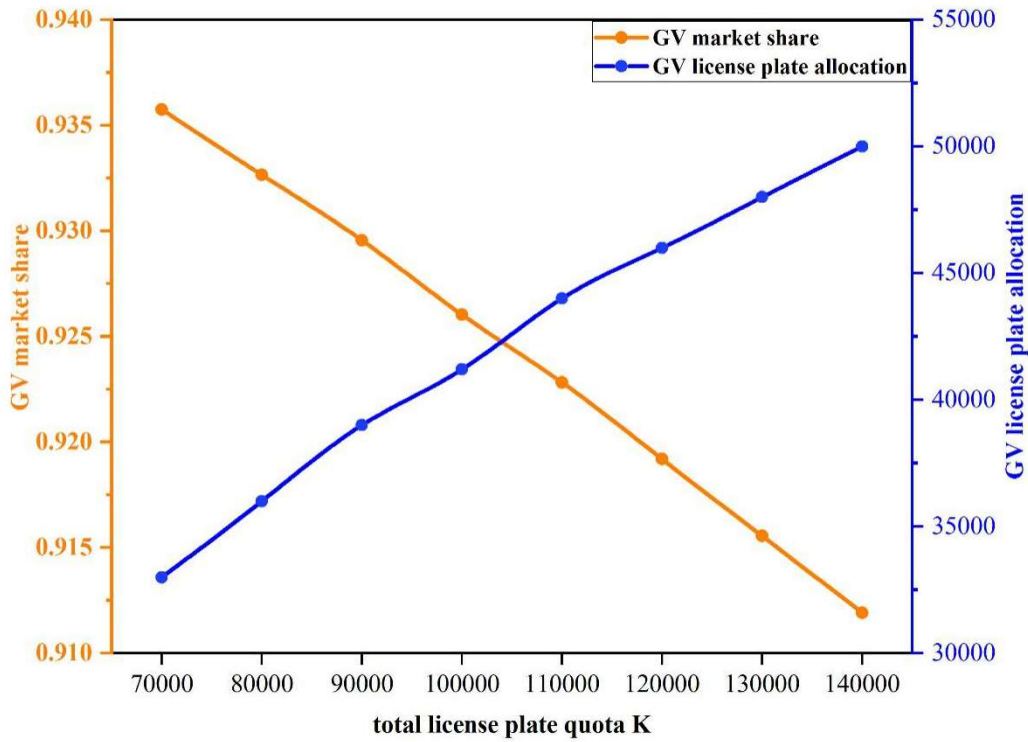


Fig.6. The influence of total quota on GV market share and allocation.

Recently, to boost the vehicle market that underwent tremendous loss due to the Corona virus, corresponding measurements have been adopted by certain cities in China. For example, Guangzhou plans to assign another 100000 license plates to all applicants until December of 2020, whereas Beijing decides to exclusively add 20000 license plates to EV applicants.

Firstly, we analyze the impact caused by total quota variation on GV penetration. As it is shown in Fig.6, when the government enlarges total quota, the optimal GV license plates quantity increases, whereas the GV market share declines. In other words, the increment in total quota contributes to the promotion of EV diffusion.

Secondly, given the distinct incentives issued by Guangzhou and Beijing respectively, we naturally speculate which is more effective in promoting EV? To answer this question, two scenarios are proposed respectively: In the first scenario, we assume that 20000 license plates would be solely distributed to EV applicants. According to the optimization model we proposed in section 3, the EV market share in this situation would be improved by 10.5%. In the second scenario, we assume to add 20000 license plates to total quota, which could increase the EV market share by only 9.3% according to our model. The variations in license plate assignment and EV market share are depicted within Fig.7.

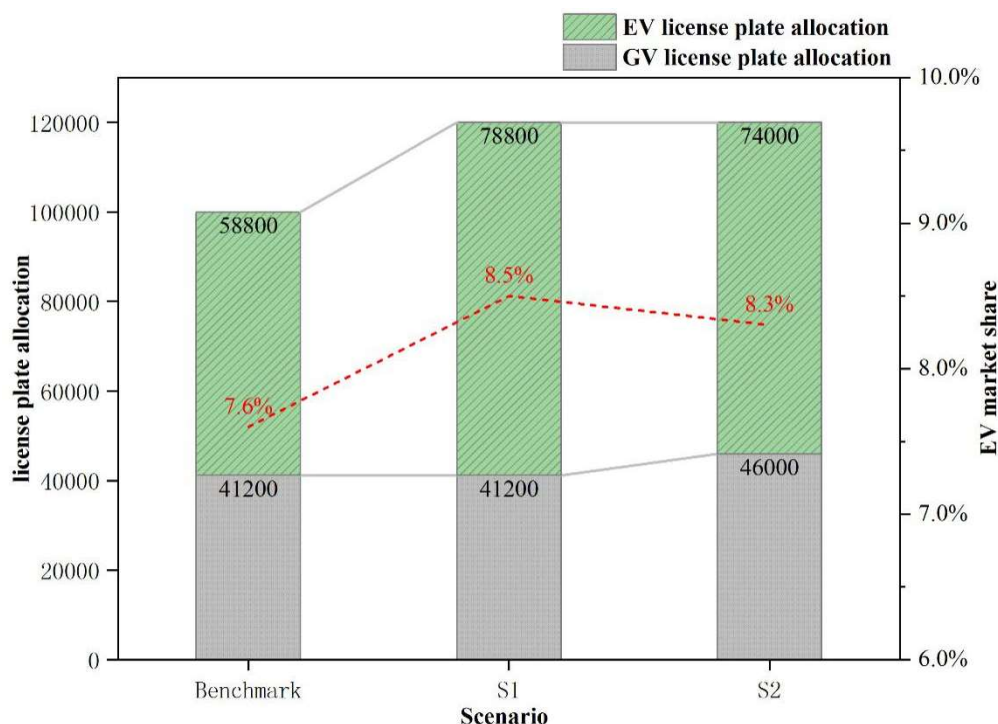


Fig.7. License plate allocations and EV market shares under different scenarios

Fig.7 indicates that assigning license plates to EV applicants exclusively is significantly more effective in improving EV diffusion. Not only does this incentive satisfy the car ownership needs of citizens, but it also stimulates the EV market which has been suffering from the phasing-out subsidies and the Corona virus. Moreover, there is a strong signal that Beijing government tends to promote EV diffusion rather than GV in the future, suggesting that more license plates would be assigned to EV exclusively. Given this tendency, many vehicle applicants in Beijing would switch their applications from GV license plates to EV license plates, considering a comparatively shorter time period to obtain an EV license plate. Consequently, the sales of EVs would surge and eventually lead to a higher rate of diffusion.

## **5.2 The impact of energy prices on EV penetration**

In order to explore the impact of electricity price on EV penetration, three electricity price levels (0.4 CNY/kWh, 0.6 CNY/kWh, and 0.8 CNY/kWh) are proposed within this part.

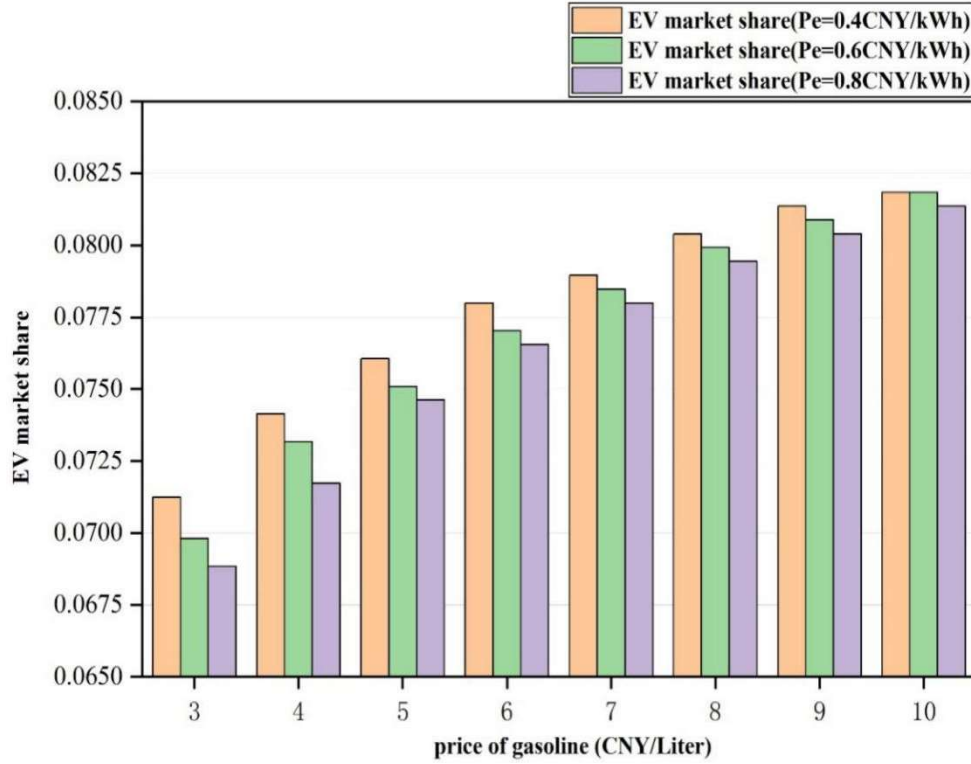


Fig.8. Impact of electricity price on EV penetration under different gasoline prices.

Fig.8 depicts the influence of electricity and gasoline prices on EV diffusion. As it is shown in Fig.8, the diffusion gap contracts when gasoline price increases. In more detail, given a relatively low gasoline price level (3 or 4 CNY/liter for instance), gap in market shares between the highest and lowest electricity price scenarios is 0.2% approximately; when the gasoline price is higher (9 or 10 CNY/liter), that gap almost disappears. In this situation, the cost of electricity consumed by EV is much less than that of gasoline consumed by GV if covering the same distance. Therefore, most applicants would be less sensitive to the electricity price and choose EV without any hesitation, accounting for the disappearance of the gap.

For example, given the current gasoline and electricity prices, a 33% reduction of the gasoline price (which will be 3.55 CNY/liter) would reduce the EV market share to 7.17%. In this scenario, the EV

market share could raise by 5% when the government reduces the electricity price from 0.6 to 0.4 CNY/kWh, which suggests that the effect caused by electricity price reduction on EV diffusion is significant. It implies that the government could promote EV diffusion effectively by reducing electricity price when the gasoline price is low.

By comparison, a 33% increment of the gasoline price (which will be 7.05 CNY/month) contributes to the improvement of EV market share by 7.87%. Nevertheless, by reducing the electricity price in the same way with the previous scenario, the EV market share could only be expanded by only 0.6%, indicating that it would be less efficient in improving EV diffusion by reducing electricity price when the gasoline price is high. Under this circumstance, to increase the competitiveness of EV, more attention should be focused on reducing the production cost of EVs, such as the cost of EV battery (Ajanovic, 2015) or engine.

### **5.3 The impact of vehicle rental fee on EV penetration**

Each year, plenty of applicants fail to obtain license plates due to the LPC policy in Beijing and we assume that they tend to rent vehicles as an alternative approach to achieve similar experience as those who have owned vehicles. Therefore, the rental expense they afford is considered as the implementary cost of the LPC policy. Given the fact that total rental expense would influence social welfare inevitably, the role vehicle rental fee play on EV diffusion should be explored within this part. In order to simulate the influence of rental fee variation on EV market share, two rental fee levels are considered: the benchmark rental fee (C1) is 2377 CNY/month and that an approximate 33% reduction of the benchmark (C2) is 1577 CNY/month. Based on the calculation results from the Eq. (14), the market share of EV would increase from 7.6% to 7.9% accordingly. The result is intriguing since it

indicates that the government could improve EV penetration by reducing the rental fee. In order to figure out the mechanism behind it, we compare the rental expenses of individual applicant under two rental fees depicted in the Fig. 9.

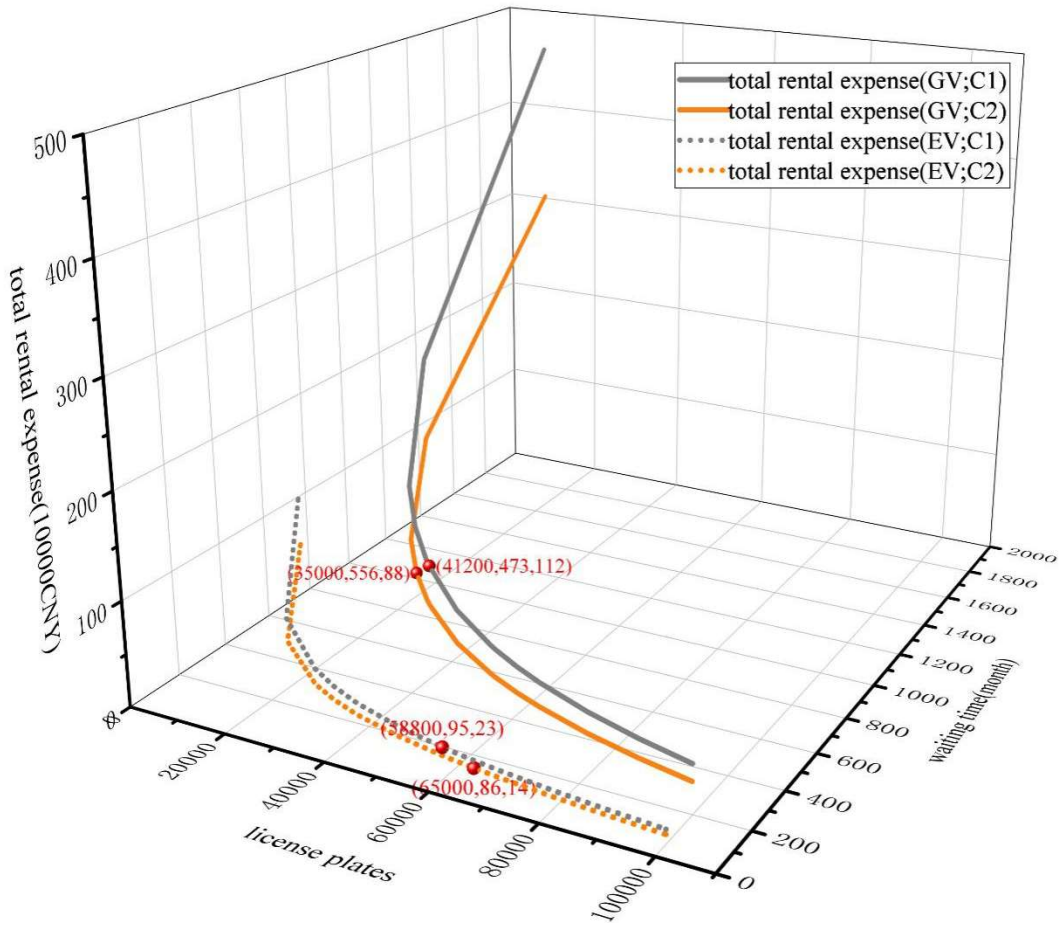


Fig.9. License plate allocations and rental expenses under different rental fees

As it is shown in Fig. 9, when the current rental fee reduces from 2377 CNY/month to 1577 CNY/month, the license plate quantity of EV would increase from 58800 to 65000, according to the optimization model. On the basis of Eq. (11), the waiting time for EV applicants would decline from 95 months to 86 months. Consequently, the individual rental expense would decrease from 225815

CNY to 135622 CNY, which means a 40% saving for each EV applicant. In contrast, the declining rental fee would lead to a reduction of GV license plates (from 41200 to 35000) and hence a much longer waiting time for GV (from 473 months to 556 months). But the lower rental fee could also bring a significant saving to each GV applicant, since the rental expense would be dropped from 1124321 CNY to 876812 CNY.

In other words, a lower renting fee would help to improve EV diffusion because of more EV licenses, less waiting time and significant rental expense savings. Furthermore, the reduction of rental expense means less financial burden for GV applicants.

Consequently, certain measurements stimulating the growth of Beijing's vehicle rental industry so as to reduce the vehicle rental fee should be considered by the policy-makers. First, under the current phasing-out EV subsidy policy in China, more subsidies should be transferred from EVs and infrastructures to vehicle rental industry. Second, a data-sharing system between the government and rental enterprises should be promoted to guarantee the transparency of the whole rental market and to improve the efficiency of government intervention.

## **6. Conclusion and Policy Implication**

This study quantified EV adoption in Beijing under the LPC policy. A two-level Stackelberg game was proposed to model the interaction between vehicle applicants and the government. The results obtained indicate some important implications for policy-makers.

- (1) Given the recent total license plate quota (100000), the optimal GV license plate quantity is 41200, whereas that of EV would be 58800. After optimization, EV market share could be 7.6%,

an approximate 15% higher than that in 2019 (6.6%<sup>6</sup>).

- (2) Increment in the total license plate quota could contribute to higher EV penetration. Furthermore, for Beijing government, assigning license plates to EV applicants exclusively is significantly more efficient in promoting EV diffusion. Not only does the incentive meet the vehicle ownership needs of citizens, but it also stimulates EV market suffered from the phasing-out subsidies and Corona virus. In this situation, many vehicle applicants in Beijing should switch their applications from GV license plates to EV license plates, considering a comparatively shorter time period to obtain an EV license plate, which contributes to a higher EV diffusion.
- (3) When gasoline price is comparatively low, vehicle applicants are more sensitive to electricity price variation, indicating that it would be more efficient for the government to enlarge EV penetration by reducing electricity price. Given a higher gasoline price, however, the applicants would pay less attention on electricity price change. Therefore, alternative measurements should be adopted by the government so as to improve EV competitiveness, such as reducing the production cost of EV battery or engine.
- (4) It is economically viable to reduce vehicle rental fee in order to improve EV penetration. A one third reduction of the current rental fee (1577 CNY/month) would not only improve EV market share from 7.6% to 7.9% but also mitigates the rental expense of GV applicants. Consequently, policies aim to mitigate rental fee are considered: First, more subsidies should be redistributed to

---

<sup>6</sup> In 2019, the number of motor vehicles in Beijing was 6.365 million. Among them, private vehicles were 4.67 million, whereas the number of new energy vehicles reached 0.307 million. Approximately, the actual market share of EV was estimated as 6.6% ( $\frac{30.7}{467} = 0.0657$ ).

vehicle rental industry. Second, a data-sharing system between the government and rental enterprises should be improved to guarantee the transparency of the rental market and to improve the efficiency of government supervision.

## References:

- Ajanovic, A. 2015. The future of electric vehicles: prospects and impediments. Wiley interdisciplinary reviews. Energy and environment 4, 521-536. <https://doi.org/10.1002/wene.160>
- Al-Alawi, B.M., Bradley, T.H. 2013. Review of hybrid, plug-in hybrid, and electric vehicle market modeling Studies. Renewable and Sustainable Energy Reviews 21, 190-203. <https://doi.org/10.1016/j.rser.2012.12.048>
- Beijing Transport Institute. 2020. 2020 Beijing Transport Development Annual Report. <http://www.bjtrc.org.cn> (accessed 14 January, 2021).
- China Electric Vehicle Charging Infrastructure Promotion Alliance. 2020., Vol. 2020. <http://www.evcipa.org.cn/> (accessed 14 January, 2021).
- Chu, W., Im, M., Song, M.R., Park, J. 2019. Psychological and behavioral factors affecting electric vehicle adoption and satisfaction: A comparative study of early adopters in China and Korea. Transportation Research Part D: Transport and Environment 76, 1-18. <https://doi.org/10.1016/j.trd.2019.09.009>
- Clinton, B., Brown, A., Davidson, C., Steinberg, D. 2015. Impact of Direct Financial Incentives in the Emerging Battery Electric Vehicle Market: A Preliminary Analysis. <https://www.nrel.gov/docs/fy15osti/63263.pdf> (accessed 14 January, 2021).
- Diamond, D. 2009. The impact of government incentives for hybrid-electric vehicles: Evidence from US states. ENERGY POLICY 37, 972-983. <https://doi.org/10.1016/j.enpol.2008.09.094>
- Djalante, R., Djalante, S. 2012. Derk Loorbach: Transition management, new mode of governance for sustainable development. Natural hazards (Dordrecht) 62, 1339-1341. <https://doi.org/10.1007/s11069-012-0126-4>
- Egnér, F., Trosvik, L. 2018. Electric vehicle adoption in Sweden and the impact of local policy instruments. ENERGY POLICY 121, 584-596. <https://doi.org/10.1016/j.enpol.2018.06.040>
- Figenbaum, E. 2017. Perspectives on Norway' s supercharged electric vehicle policy. ENVIRON INNOV SOC TR 25, 14-34. <https://doi.org/10.1016/j.eist.2016.11.002>
- Gneezy, U., Meier, S., Rey-Biel, P. 2011. When and Why Incentives (Don't) Work to Modify Behavior. J ECON PERSPECT 25, 191-210. <http://dx.doi.org/10.1257/jep.25.4.191>
- He, X., Zhan, W., Hu, Y. 2018. Consumer purchase intention of electric vehicles in China: The roles of perception and personality. J CLEAN PROD 204, 1060-1069. <https://doi.org/10.1016/j.jclepro.2018.08.260>
- Helveston, J.P., Liu, Y., Feit, E.M., Fuchs, E., Klampf, E., Michalek, J.J. 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the U.S. and China. Transportation Research Part A: Policy and Practice 73, 96-112. <http://dx.doi.org/10.1016/j.tra.2015.01.002>
- Hou, C., Wang, H., Ouyang, M. 2013. Survey of daily vehicle travel distance and impact factors in Beijing. IFAC Proceedings Volumes 46, 35-40. <https://doi.org/10.3182/20130904-4-JP-2042.00002>

- Hou, X., Peng, S., Ma, Y. 2013. Cost Analysis of and Comparison between Beijing's Car Plate Lottery and Shanghai's License Auction. China soft science magazine, 58-65.<http://dx.chinadoi.cn/10.3969/j.issn.1002-9753.2013.11.007>.
- Jang, D., Kim, B., Lee, S. 2018. A two-sided market platform analysis for the electric vehicle adoption: Firm strategies and policy design. Transportation Research Part D: Transport and Environment 62, 646-658. <https://doi.org/10.1016/j.trd.2018.02.002>
- Javid, R.J., Nejat, A. 2017. A comprehensive model of regional electric vehicle adoption and penetration. TRANSPORT POLICY 54, 30-42. <https://doi.org/10.1016/j.tranpol.2016.11.003>
- Jenn, A., Springel, K., Gopal, A.R. 2018. Effectiveness of electric vehicle incentives in the United States. ENERG POLICY 119, 349-356. <https://doi.org/10.1016/j.enpol.2018.04.065>
- Kong, W., Li, Q., Wang, X. 2012. Analysis on Energy Saving and Emission Reduction of Electric Vehicles Based upon Life-Cycle Energy Efficiency. Electric Power 45, 64-67.<http://dx.chinadoi.cn/10.3969/j.issn.1004-9649.2012.09.015>
- Lin, B., Wu, W. 2018. Why people want to buy electric vehicle: An empirical study in first-tier cities of China. ENERG POLICY 112, 233-241. <https://doi.org/10.1016/j.enpol.2017.10.026>
- Ma, S., Fan, Y., Feng, L. 2017. An evaluation of government incentives for new energy vehicles in China focusing on vehicle purchasing restrictions. ENERG POLICY 110, 609-618. <http://dx.doi.org/10.1016/j.enpol.2017.07.057>
- Mersky, A.C., Sprei, F., Samaras, C., Qian, Z.S. 2016. Effectiveness of incentives on electric vehicle adoption in Norway. Transportation Research Part D: Transport and Environment 46, 56-68. <http://dx.doi.org/10.1016/j.trd.2016.03.011>
- Ouyang, D., Zhang, Q., Ou, X. 2018. Review of Market Surveys on Consumer Behavior of Purchasing and Using Electric Vehicle in China. Energy Procedia 152, 612-617. <https://doi.org/10.1016/j.egypro.2018.09.219>
- Pacific Automotive Network. 2020. Quotation of small vehicle, Vol. 2020. <https://price.pcauto.com.cn/price/q-k110.html>(accessed 14 January 2021).
- Qin, Z., Zhu, G. 2015. A marketing Analysis of Electric Vehicles Based on Trilateral Game among Government, Enterprises and Applicants. Industrial Engineering Journal 18, 1-8. <http://dx.chinadoi.cn/10.3969/j.issn.1007-7375.2015.04.001>
- Sheldon, T.L., Dua, R. 2020. Effectiveness of China's plug-in electric vehicle subsidy. ENERG ECON 88, 104773. <https://doi.org/10.1016/j.eneco.2020.104773>
- Sierzechula, W., Bakker, S., Maat, K., van Wee, B. 2014. The influence of financial incentives and other socio-economic factors on electric vehicle adoption. ENERG POLICY 68, 183-194. <http://dx.doi.org/10.1016/j.enpol.2014.01.043>
- Silvia, C., Krause, R.M. 2016. Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. ENERG POLICY 96, 105-118. <http://dx.doi.org/10.1016/j.enpol.2016.05.039>
- The People's Government of Beijing Municipality. 2020. Beijing Municipal Passenger Car Index Regulation Management Information System., Vol. 2020. <https://www.bjhjyd.gov.cn/jggb/index.html> (accessed 14 January, 2021).
- The State Council of the People's Republic of China. 2020. China raises gasoline, diesel retail prices, Vol. 2020. <https://www.gov.cn/shuju/jiage/youjia.htm> (accessed 14 January, 2021).

- Tietge, U. 2017. Lessons learned from Sweden's electric vehicle roller-coaster. The international Council on Clean Transportation. <https://theicct.org/blog/staff/lessons-learned-sweden-EV-rollercoaster> (accessed 14 January, 2021).
- Wang, N., Tang, L., Pan, H. 2017. Effectiveness of policy incentives on electric vehicle acceptance in China: A discrete choice analysis. *Transportation Research Part A: Policy and Practice* 105, 210-218. <http://dx.doi.org/10.1016/j.tra.2017.08.009>
- Wang, N., Tang, L., Pan, H. 2019. A global comparison and assessment of incentive policy on electric vehicle promotion. *SUSTAIN CITIES SOC* 44, 597-603. <https://doi.org/10.1016/j.scs.2018.10.024>
- Wang, S., Zhao, J. 2017. The distributional effects of lotteries and auctions—License plate regulations in Guangzhou. *Transportation Research Part A: Policy and Practice* 106, 473-483. <http://dx.doi.org/10.1016/j.tra.2017.10.011>
- Yang, J., Liu, A.A., Qin, P., Linn, J. 2020. The effect of vehicle ownership restrictions on travel behavior: Evidence from the Beijing license plate lottery. *J ENVIRON ECON MANAG* 99, 102269. <https://doi.org/10.1016/j.jeem.2019.102269>
- Yang, J., Liu, Y., Qin, P., Liu, A.A. 2014. A review of Beijing's vehicle registration lottery: Short-term effects on vehicle growth and fuel consumption. *ENERG POLICY* 75, 157-166. <https://doi.org/10.1016/j.enpol.2014.05.055>
- Yu, Z., Li, S., Tong, L. 2016. Market dynamics and indirect network effects in electric vehicle diffusion. *Transportation Research Part D: Transport and Environment* 47, 336-356. <http://dx.doi.org/10.1016/j.trd.2016.06.010>
- Yuan, X., Liu, X., Zuo, J. 2015. The development of new energy vehicles for a sustainable future: A review. *Renewable and Sustainable Energy Reviews* 42, 298-305. <https://doi.org/10.1016/j.rser.2014.10.016>
- Zhang, X. 2014. Reference-dependent electric vehicle production strategy considering subsidies and consumer trade-offs. *ENERG POLICY* 67, 422-430. <https://doi.org/10.1016/j.enpol.2013.12.028>
- Zhang, X., Bai, X., Zhong, H. 2018. Electric vehicle adoption in license plate-controlled big cities: Evidence from Beijing. *J CLEAN PROD* 202, 191-196. <https://doi.org/10.1016/j.jclepro.2018.07.265>
- Zhang, X., Bao, T., Yu, T., Yang, B., Han, C. 2017. Deep transfer Q-learning with virtual leader-follower for supply-demand Stackelberg game of smart grid. *ENERGY* 133, 348-365. <https://doi.org/10.1016/j.energy.2017.05.114>
- Zhu, L., Wang, P., Zhang, Q. 2019. Indirect network effects in China's electric vehicle diffusion under phasing out subsidies. *APPL ENERG* 251, 113350. <https://doi.org/10.1016/j.apenergy.2019.113350>
- Zhu, L., Zhang, Q., Lu, H., Li, H., Li, Y., McLellan, B., Pan, X. 2017. Study on crowdfunding's promoting effect on the expansion of electric vehicle charging piles based on game theory analysis. *APPL ENERG* 196, 238-248. <http://dx.doi.org/10.1016/j.apenergy.2016.11.060>
- Zhuge, C., Wei, B., Shao, C., Shan, Y., Dong, C. 2020. The role of the license plate lottery policy in the adoption of Electric Vehicles: A case study of Beijing. *ENERG POLICY* 139, 111328. <https://doi.org/10.1016/j.enpol.2020.111328>

## Appendices:

### Appendix A

#### The threshold of GV market share

For individual vehicle applicant, the utility functions of purchasing EV and GV are defined as:

$$U_G = \beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + \beta_4 * N_G / (6 * B_G) + \varepsilon_G$$

$$U_E = \beta_1 * P_E + \beta_2 * I_E + \beta_4 * (K - N_G) / B_E + \varepsilon_E$$

Moreover, considering the specific relationship between the random variables from Eq. (3), we substitute  $\varepsilon_G$  with  $\varepsilon_E$  into the following equation:

$$\beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + \beta_4 * N_G / (6 * B_G) + \varepsilon_G = \beta_1 * P_E + \beta_2 * I_E + \beta_4 * (K - N_G) / B_E + \varepsilon_E$$

Eq. (A.1)

The algebra expression of  $\eta^*$  is:

$$\eta^* = \frac{(\beta_1 * P_G + \beta_2 * I_G + \beta_3 * M_G + 1 - \beta_1 * P_E - \beta_2 * I_E - \beta_4 * (\frac{K}{B_E}) + \beta_4 * (\frac{1}{B_G} + \frac{1}{B_E}) * N_G)}{2}$$

### Appendix B

#### The duration model

For individual GV applicant, the distribution function of the applicant's waiting time,  $F(t)$ , denotes the possibility of winning a license plate within  $t$  term of lottery.  $f(t)$  refers to the probability density function correspondingly.  $S(t)$  defined as the survival function measures the possibility that applicant fails to win a license plate within  $t$  terms of lotteries:

$$S(t) = 1 - F(t) = P(T > t) \quad \text{Eq. (B. 1)}$$

The hazard function  $K(t)$  denoting the possibility that applicant fails to win a license plate in  $t$  terms of lotteries but win one within time interval  $(t, t+h)$  is defined as:

$$K(t) = \lim_{h \rightarrow 0} \frac{P(t \leq T \leq t+h | T \geq t)}{h} = \lim_{h \rightarrow 0} \frac{P(t \leq T \leq t+h)}{h * P(T \geq t)} = \lim_{h \rightarrow 0} \frac{F(t+h) - F(t)}{h * S(t)} = -\frac{\partial \ln S(t)}{\partial t} \quad \text{Eq. (B.2)}$$

By modifying the equation, we obtain a first-order differential equation shown as below:

$$\frac{dS(t)}{dt} + S(t) * K(t) = 0 \quad \text{Eq. (B.3)}$$

$S(t)$  could be derived by solving the equation Eq. (12):

$$S(t) = \int (K(t) * e^{-\int_0^t K(m) dm}) dt \quad \text{Eq. (B.4)}$$

Correspondingly, the probability density function could be obtained:

$$f(t) = K(t) * e^{-\int_0^t K(m) dm} \quad \text{Eq. (B.5)}$$

Based on the duration model, if the probability of winning a license plate in each lottery is  $p$ , the hazard function  $K(t)$  should be expressed as:

$$K(t) = (1 - p)^t * p \quad \text{Eq. (B.6)}$$

By substituting Eq. (15) in Eq. (14), we could obtain the algebra expression of the possibility density function  $f(t)$ :

$$f(t) = (1 - p)^t * p * e^{\frac{p * (1 - (1 - p)^t)}{\ln(1 - p)}} \quad \text{Eq. (B.7)}$$

Since there are 6 lotteries held in each year, the expected waiting time of GV applicant is:

$$E(T_G) = \left( \int_0^{+\infty} t * f(t) dt \right) * \frac{1}{6} = \left( \int_0^{+\infty} t * (1 - p)^t * p * e^{\frac{p * (1 - (1 - p)^t)}{\ln(1 - p)}} dt \right) * \frac{1}{6}$$