A Less Fuel Efficient Fleet: Unintended Consequences of Beijing's Vehicle Lottery System*

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Abstract

To control vehicle growth and air pollution, Beijing imposed a vehicle lottery system (VLS) in January 2011, which randomly allocated a quota of licenses to lottery participants. Specifically, this paper investigates the effect of this policy on fleet composition. Using car registration data, we estimate a random coefficient discrete choice model and conduct counterfactual analysis based on the estimated parameters. We find that the VLS shifted new auto purchases towards high-end but less fuel-efficient vehicles. Our theoretical analysis also suggests that high income households are more likely to enter the lottery under VLS, hence increasing the proportion of high-end vehicle demand.

KEYWORDS: Vehicle Lottery System; Fleet Composition; Fuel Efficiency

JEL CLASSIFICATION: H23; L62; Q51; Q58; R48.

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1 Introduction

China's automobile industry has developed rapidly since 2000. Vehicle population increased from 16.09 million units in 2000 to 62.09 million units in 2009 at an average annual rate of 14.5%.[1] The growth rate increased particularly rapidly over the last several years (17% in 2008, 21.76% in 2009, and 24.36% in 2010). However, the fast growth in vehicle ownership and usage has been accompanied by increase in energy consumption, severe air pollution, and health concerns in many cities, such as Beijing. To solve these problems, Beijing imposed a vehicle lottery system (VLS) to control vehicle population growth in January 2011. Unlike the vehicle license auction system in Shanghai, new licenses are randomly allocated through non-transferable lotteries in Beijing. Qualified applicants can enter the lottery at no cost. Only those who win the lottery have the right to register new vehicles in Beijing.[2]

Researchers investigate the effect of VLS on vehicle growth, fuel consumption, and pollutant emissions (Hao et al., 2011; Yang et al., 2014; Li and Jones, 2015). They find that VLS is effective in controlling vehicle growth. Moreover, Yang et al. (2016) estimate the effect of VLS on distance traveled and commuting time. In addition, VLS causes misallocation and welfare loss, because those without the highest willingness to pay may get the cars (Li, 2017). However, to our knowledge, no studies investigate the impact of VLS on fleet composition. It is urgent to fully understand the effect of VLS, since this policy was also adopted by Guiyang in 2011. In addition, hybrid VLS systems (combining lottery and auctions) have been implemented in other large cities in the region, and other cities (Chengdu, Chongqing, Qingdao, and Wuhan) are considering enacting similar systems.[3]

Our paper mainly focuses on the effect of Beijing's VLS on fleet composition. First, we construct and estimate a random coefficient discrete choice model developed by Berry et al. (1995) using car registration data. The model incorporates household preference heterogeneity and unobserved product attributes. To identify the effects of the VLS, we then simulate outcomes under the counterfactual scenario of no policy and compare them with the

[1] The average growth rate of vehicle population in the United States from 2000 to 2009 was 1.19%.

[2] Those residents who scrap or sell their existing cars can keep their licenses, and thus do not need to enter the lottery.

[3] Guangzhou, Tianjin, Hangzhou, and Shenzhen implemented hybrid systems in July 2012, January 2014, May 2014, and December 2014, respectively.

observed facts. Our result indicates that VLS changed fleet composition, skewing it towards high-end and less fuel-efficient vehicles. In particular, our estimates indicate that the sales-weighted average price of cars registered in Beijing in 2012 under the VLS was about 62,440 Yuan (US$9,141) higher than under no policy. The fleet fuel efficiency is 12.85 km/L under the lottery system, relative to 13.41 km/L under no policy. Then we use a theoretical model to offer a possible explanation for this result. We find that high income households are more likely to enter the lottery and therefore intend to buy high-end vehicles.

Related literature. Our paper is related to studies by Seik (1998), Xiao and Zhou (2013) and Xiao et al. (2017), who analyze vehicle quota systems by auction. Seik (1998) investigates impacts of Singapore's vehicle quota system on vehicle population, car prices and traffic congestion; whereas Xiao and Zhou (2013) and Xiao et al. (2017) examine the environmental and welfare consequences of Shanghai's vehicle auction system. This paper focuses on Beijing's VLS which is a non-market based mechanism allocating the quota of vehicle licenses through lottery, while Shanghai's vehicle quota system allocates license plates using an auction, where households with the highest willingness to pay may be more likely to obtain quota.

Recently, some studies find that the VLS is effective in controlling on vehicle growth, fuel consumption, and pollutant emissions (Yang et al., 2014; Li and Jones, 2015). In addition, Li (2017) conducts a welfare analysis of Beijing's VLS and finds that, compared with a uniform price auction, Beijing's VLS led to a welfare loss of nearly 36 billion Yuan (U.S. $6 billion) in Beijing in 2012. However, little is known about the impact of Beijing's VLS on fleet composition. Even less is known about why the VLS changes fleet composition. Our study contributes to this literature.

Our study also adds to the empirical literature on vehicle-related policies. Most of the literature focuses on fuel taxes (Parry and Small, 2005; Fullerton and Gan, 2005; Bento et al., 2009; Xiao and Ju, 2014), consumption taxes (Xiao and Ju, 2014), congestion fees and road pricing (Small et al., 2005; Eliasson et al., 2009; Gibson and Carnovale, 2015), driving restrictions (Davis, 2008; Gallego et al., 2013; Viard and Fu, 2015), corporate average fuel economy (Goldberg, 1998), and Low Emission Zones (Wolff and Perry, 2010; Wolff, 2014). Our analysis helps both policymakers and researchers better understand the impacts of VLS, enabling comparison of policies and indicating applicable policies for both China and other countries with large metropolitan areas to address problems.

The rest of the paper is organized as follows. Section 2 briefly reviews Beijing's VLS, and introduces the data. Section 3 describes the empirical model and the estimation strategies. Section 4 reports our estimation results and counterfactual analysis. Section 5 concludes.

2 Policy and Data Description

2.1 Policy Description

To reduce traffic congestion and air pollution, Beijing issued a plan to control vehicle registrations on December 13, 2010. On December 23, 2010, Beijing municipal government froze new registrations and announced that, from January 2011, before purchasing a vehicle, residents and corporations need to enter a publicly held lottery and win a license plate, which is necessary to register a vehicle. Each month, there are about 20,000 license plates to allocate, among which, about 88% (or 17,600) are assigned to private vehicles and the rest for institutions. The licenses are allocated through random drawings under a monthly lottery-style quota system for private applicants and every two months for businesses.

The lotteries for private licenses are held on the 26th day of each month. Licenses are needed for first-time buyers, second-hand vehicle buyers, and those who accept gifted vehicles or transfer out-of-state registration to Beijing. Those who destroy, sell, or trade-in their existing cars, can retain their license plates to register new vehicles. The eligible participants include Beijing residents, and non-residents with temporary residence permits who have been paying social insurance and income tax for at least five years in Beijing. Individuals who have registered vehicles cannot enter the lottery. However, if a household with a car has a second driver, this driver can enter the lottery. To enter the lottery, applicants can fill forms on a government website[4] or apply at a walk-in service center without cost.

Beijing's Municipal Commission of Transport publishes the lottery results on the lottery

[4] `http://www.bjhjyd.gov.cn/`.

system's website. Each winner can download a certificate online or pick it up at a walk-in service center. The certificate allows the quota holder to purchase a license plate and register a vehicle. Licenses cannot be transferred or sold. Each quota is valid for six months. If a lottery winner does not register a vehicle during this period, the license will be added to the pool of quotas in the next lottery. Those who allow their quotas to expire cannot participate in the lottery within the next three years.

To strictly enforce the vehicle lottery, additional policies are issued to prevent Beijing residents from registering vehicles in nearby cities while driving in Beijing. Out-of-state vehicles need to obtain temporary driving permits to enter the 5th ring road.[5] Moreover, these vehicles are banned to travel within the 5th ring road (inclusively) during peak hours.

2.2 Data

2.2.1 Data Description

There are two main data sources for our analysis. The first data set contains monthly vehicle registration data in Beijing, Nanjing, Shenzhen, and Tianjin.[6] The second data set consists of household income distributions in each city. Our sample is from January 2009 to December 2012.

Vehicle data. The monthly new passenger vehicle registration information is from Dalian Wismar Information Co., Ltd.[7] This data set includes manufacturer, brand, model year, model, engine size, car bodystyle, quantity, and purpose of use (private or business).[8]

In this paper, we focus on passenger vehicles and, hence, we drop observations registered for business use since business consumers are quite different from private consumers. We aggregate the monthly data into quarterly levels and use the total sales and average quarterly prices for each quarter to measure their sales and prices. A product is defined as a unique combination of the model year, manufacturer, brand, model, engine size, and

[5]The 5th ring road is about 98.58 km in length and the area within it is about 700 km^2.

[6]Li (2017) also uses Nanjing and Tianjin as control cities given their similarities with Beijing.

[7]In China, vehicle registration data are not released to the public. We bought the data from Dalian Wismar Information Co., Ltd, which collects and analyzes market data. The data provider required us not to release the data.

[8]Vehicle bodystyle includes sedan, SUV, MPV, station wagon, and coupe.

bodystyle. Consequently, there are 2,141 different products in our analysis. Our sample also yields 38,359 observations (city-year-quarter-product).

To complete the data set, we collect vehicle attribute data from the website auto.sohu.com and Car Market Guide, which help us obtain the fuel consumption factors for each type of vehicle. Transaction prices are not available. As suggested by Li et al. (2015) and Li (2017), Manufacturer Suggested Retail Prices (MSRP) can be good proxy for retail prices.[9] The data set also includes horsepower (in kilowatts), car weight (in 1,000 kilograms), vehicle size (in m^2), fuel efficiency (in km/liter), and engine size (in Liters). In addition, we also obtain gasoline prices from National Development and Reform Commission of China to construct a gas expenditure variable, which measures consumers' expenditures on gas per kilometer driven. All prices are in 2012 RMB Yuan. We use the Consumer Price Index to deflate.[10] Table 1 provides the summary statistics of our sample. The sales-weighted average price is 199,600 Yuan, which is higher than the average household income.[11]

Table 1: Summary Statistics of Vehicle Data 2009-2012

Variables	Mean	S.D.	Min	Max
Quarterly sales by product	117.42	300.82	1	6,620
Price (1,000 Yuan)	199.60	192.97	29.09	2197.41
Weight (1,000 kg)	1.37	0.29	0.65	2.89
Horsepower (kw)	100.74	34.10	26.50	250.00
Vehicle size (m^2)	8.02	0.90	4.20	11.57
Fuel efficiency (km/liter)	13.02	2.17	5.24	37.04
Gas expenditure (Yuan/km)	0.53	0.10	0.16	1.42
Engine size (L)	1.84	0.50	0.80	5.70

Note: All money is in 2012 RMB Yuan. The number of observations is 38,359. The mean of price, weight, horsepower, vehicle size, fuel efficiency, gas expenditure, and engine size are sales-weighted means.

Household income distribution. Household income would significantly affect vehicle purchase decisions. It also causes households' heterogeneous preferences over prices. However, household income data are not open to the public in China. To control for household

[9]More discussions about MSRP can be found in Li (2017).

[10]Consumer Price index are from National Bureau of Statistics of the People's Republic of China.

[11]Vehicle prices are computed based on MSRP and taxes. Taxes include consumption tax (please refer to Xiao and Ju (2014) for more details), value-added tax (17%), and sales tax. In 2009 and 2010, the sales tax was reduced to 5 and 7.5 percent for vehicles with engine displacement no more than 1.6 liter, respectively. After 2011, these tax deductions were canceled.

heterogeneity, we follow Li et al. (2015) and construct household income distribution in each city and year through the Chinese Household Income Survey (2007) and annual statistical yearbooks of each city.[12]

2.2.2 Stylized Facts

The above summary statistics do not show the changes of vehicle characteristics across the cities over time. Figure 1-3 display quarterly average prices, horsepower, and fuel efficiency, respectively. As shown in Figure 1, before 2011, Shenzhen has the highest sales-weighted average price, followed by Beijing, while Tianjin has the lowest.[13] However, the sales-weighted average price in Beijing increases from 194,529 Yuan before January 2011 to 249,245 Yuan after January 2011, representing a 28.13% increase. After the policy was announced, Beijing ranks first in sales-weighted average price. Specifically, during the post policy period, the sales-weighted average price of Beijing is about 8.52% higher than that of Shenzhen, 29.28% higher than that of Nanjing, and 59.92% higher than that of Tianjin. From Figure 2 and 3, we can find that sales-weighted average horsepower and fuel efficiency follow similar patterns as sales-weighted average prices. These stylized facts suggest that Beijing's VLS may affect the composition of the fleet, increasing the proportion of high-end, more powerful, but less fuel-efficient cars.

However, the changes mentioned above could be caused by other factors, such as household income. Our analysis employs a random coefficient discrete choice model to control these factors and identify the effects of the vehicle lottery on fleet composition in Beijing.

[12]We obtain household income levels from the yearbooks. In Beijing, households are divided into five income levels: low income households (first quintile), medium-low income households (second quintile), medium income households (third quintile), medium-high income households (fourth quintile), and high income households (fifth quintile). Nanjing, Shenzhen, and Tianjin use seven income levels: lowest income households (first decile), low income households (second decile), medium-low income households (second quintile), medium income households (third quintile), medium-high income households (fourth quintile), high income households (ninth decile), and highest income households (tenth decile). Please refer to Li et al. (2015) for more details about the procedures to construct household income distribution.

[13]In particular, the sales-weighted average price of Beijing was about 7.73% lower than that of Shenzhen, 11.34% higher than that of Nanjing, and 36.24% higher than that of Tianjin.

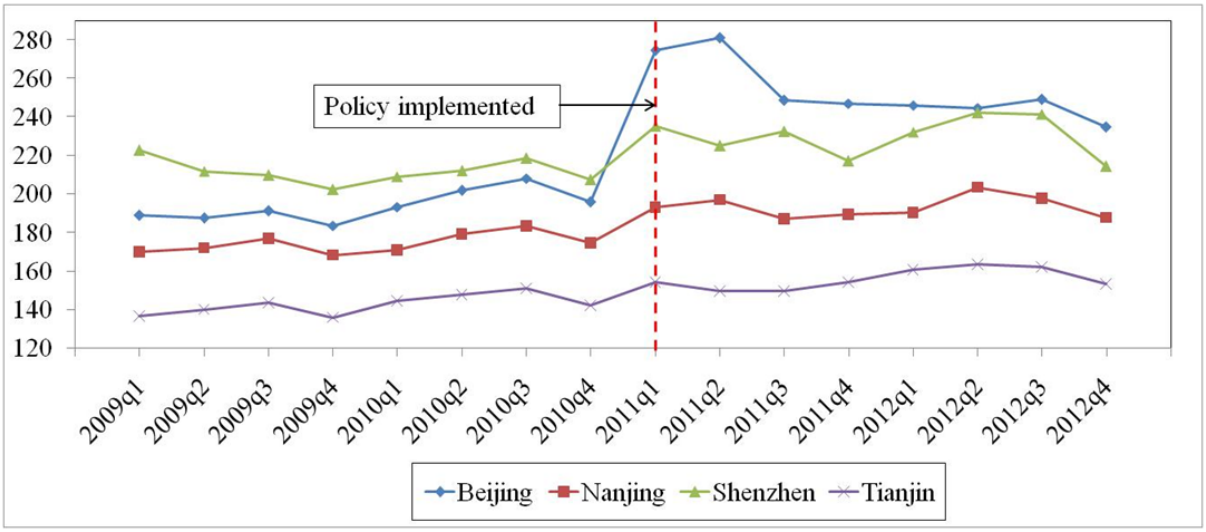

Figure 1: Quarterly Sales-weighted Average Prices (1,000 Yuan) 2009-2012 in Four Cities

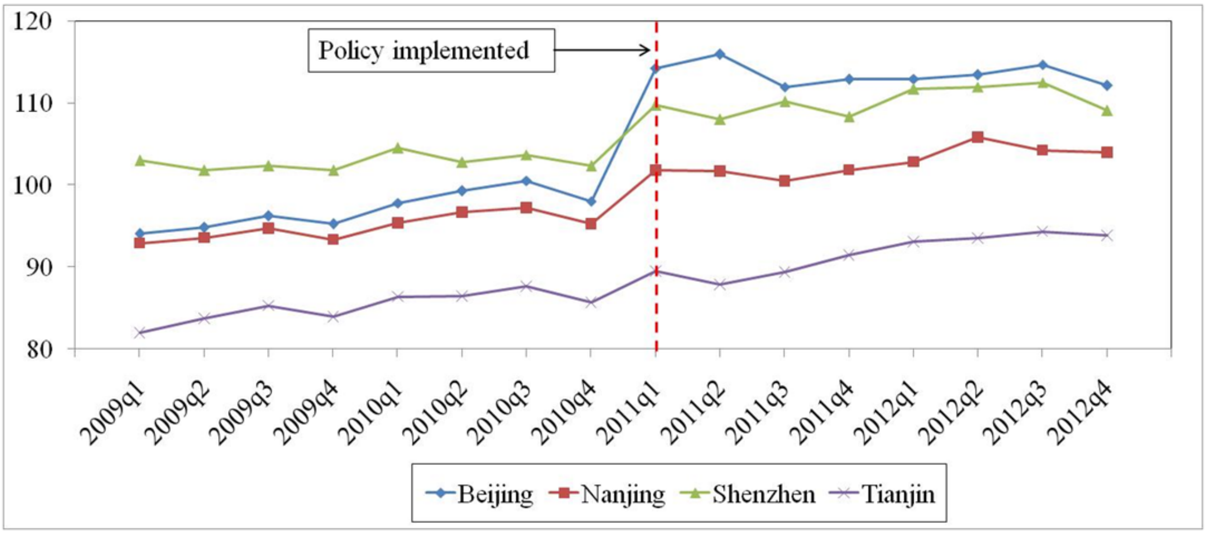

Figure 2: Quarterly Sales-weighted Average Horsepower (kw) 2009-2012 in Four Cities

3 Empirical Model and Estimation

3.1 Utility Function Specification

Our objective is to investigate the effects of Beijing's vehicle lottery. We set up and estimate a random-coefficient discrete choice model of automobile oligopoly in the spirit of Berry et al. (1995).

Let $m = 1, 2, 3, 4$ denote a market (i.e., Beijing, Nanjing, Shenzhen, and Tianjin) and t denote time (quarter by year). In market m at time t, a set of products, $j = 0, 1, ..., J$, is available. We use 0 to denote the outside option (i.e., the choice of not buying a new vehicle). Let i de-

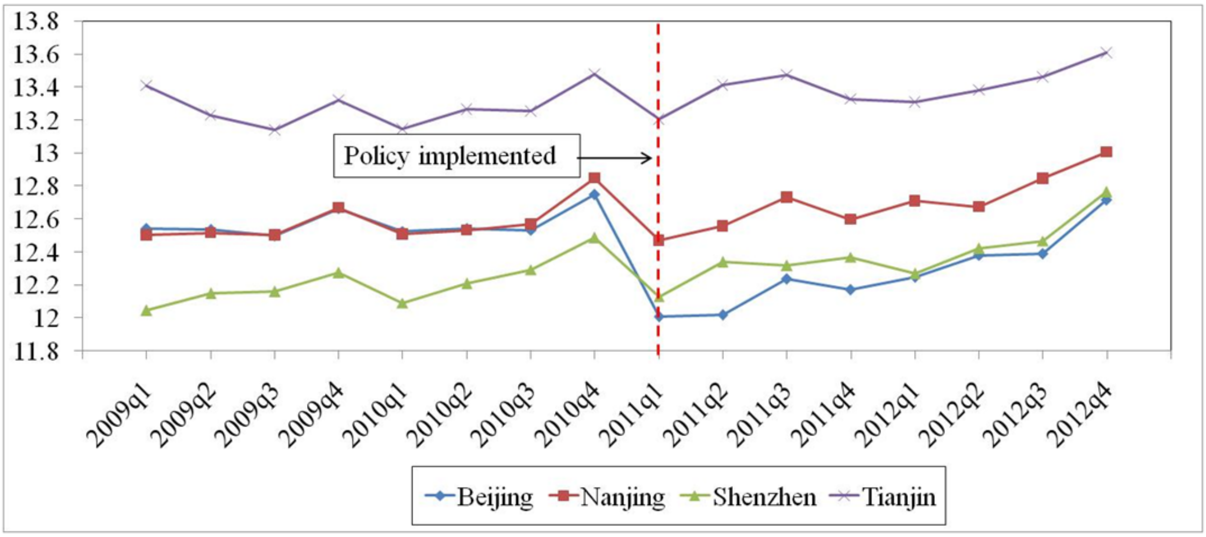

Figure 3: Quarterly Sales-weighted Average Fuel Efficiency (km/L) 2009-2012 in Four Cities

note a household. The utility from the outside option is normalized to ε_{i0mt}, which follows i.i.d. type I extreme value distribution, as in Berry et al. (1995) and Li (2017). In market m, the indirect utility of household i when purchasing product j at time t is given by

$$\begin{aligned} u_{ijmt} =& x_{jmt}\beta_i + \alpha_i \ln p_{jmt} + \lambda_{bs} dbodystyle_j + \lambda_f dfirm_j + \lambda_q dquarter \\ &+ \lambda_y dyear + \lambda_c dcity + \xi_{jmt} + \varepsilon_{ijmt} \end{aligned} \tag{1}$$

where x_{jmt} is a vector of product j's observed characteristics in market m at time t, including a constant term, logarithm of horsepower, vehicle weight, gas expenditure per km, vehicle size, and engine size. p_{jmt} is the price of product j in market m at time t. The model also includes vehicle bodystyle dummies, firm dummies, quarter dummies, year dummies, and city dummies to capture the fixed effects. ξ_{jmt} is the unobserved (to researchers) characteristics of product j in market m at time t, such as product quality. ε_{ijmt} is an independently and identically distributed (across products, households, and markets) idiosyncratic shock that is drawn from the type I extreme value distribution.

Households are heterogenous in their tastes for price and other characteristics. For example, households with higher income can be less price sensitive. Household heterogeneity is captured by random coefficients α_i and β_i. In particular, α_i is household i's marginal utility from income and it is given by

$$\alpha_i = \bar{\alpha} + \eta \ln y_{imt} + \sigma_p v_i^p \tag{2}$$

where y_{imt} is household income, and v_i^p is unobserved household characteristics that affect household preferences and follow a standard normal distribution. Since households with a higher income y_{imt} tend to be less price sensitive, we expect η to be positive.

Similarly, β_{ik} measures household-specific taste on vehicle characteristic x_{jtk}, which is the kth attribute of product j. Specifically, β_{ik} is defined as

$$\beta_{ik} = \bar{\beta}_k + \sigma_k v_i^k \tag{3}$$

where $\bar{\beta}_k$ is the average preference across households and $\sigma_k v_i^k$ captures random tastes. v_i^k is assumed to have a standard normal distribution.

Combining equations (1), (2), and (3), we obtain

$$u_{ij} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt} \tag{4}$$

where the utility function is decomposed into a mean utility

$$\delta_{jmt} = \sum_{k=1}^{K} x_{jkmt}\bar{\beta}_k + \bar{\alpha} \ln p_{jmt} + \lambda dummies + \xi_{jmt} \tag{5}$$

a household-specific utility (i.e., deviation from the mean utility)

$$\mu_{ijmt} = \sum_{k=1}^{K} \sigma_k x_{jkmt} v_i^k + (\eta \ln y_{imt} + \sigma_p v_i^p) \ln p_{jmt} \tag{6}$$

and a random taste shock ε_{ijmt}.

Every household chooses the product that maximizes his utility. As a result, the utility specifications imply that the market share for product j in market m at time t is

$$s_{jmt}(p_{mt}, X_{mt}^d, \xi_{mt}, \theta) = \int \frac{e^{\delta_{jmt} + \mu_{ijmt}} \cdot 1(saving_{imt} \geq p_{jmt})}{1 + \sum_{r=1}^{J} [e^{\delta_{rmt} + \mu_{irmt}} \cdot 1(saving_{imt} \geq p_{rmt})]} dP(y) dP(v) \tag{7}$$

where $p_{mt} = (p_{1mt},..., p_{Jmt})'$ and X^d_{mt} includes x_{jmt}, and dummy variables. θ are the model parameters, where $\theta_1 = (\bar{\alpha}, \bar{\beta}, \lambda)'$, $\theta_2 = (\sigma, \eta)'$, and $\theta = (\theta_1, \theta_2)'$. And $P(\cdot)$ denotes population distribution functions. $1(saving_{imt} \geq p_{jmt})$ is an indicator function, which is equal to 1 if a household's saving is greater than or equal to product j's price and the household can afford to buy vehicle j. Following Xiao et al. (2017), we assume saving to be five times of the household annual income, i.e., $saving_{imt} = y_{imt} \cdot 5$.[14]

If N_{mt} is the market size in market m at time t, the demand for product j is $N_{mt}s_{jmt}$. Following the literature (Berry et al., 1995, 2004), the measure of market size is the number of households in the city in a given year divided by 4.[15]

3.2 Identification and Estimation

After the idiosyncratic error term ε_{ijmt} is integrated out analytically, the econometric error term will be the unobserved product characteristics, ξ_{jmt}, such as prestige and product quality. Prices could be correlated with these product characteristics. For example, vehicles with higher quality generally have higher prices. To address the price endogeneity problem and estimate the parameters in equation (1), we employ the GMM estimation method proposed by Berry et al. (1995), which uses the moment condition

$$E(\xi_{jt}|z_{jt}) = 0 \tag{8}$$

where z_{jmt} is a vector of instrumental variables described below.

To derive ξ_{jmt}, we first need to estimate market shares. While the market share in equation (7) does not have a closed form, it can be evaluated by Monte Carlo simulation with ns

[14] See Xiao et al. (2017) for more details about reasons for saving setting.

[15] While we measure market size based on the number of households, the unit of lottery participation in the VLS is the individual. Using a different number as market size does not affect parameter estimates except for the estimate of the constant coefficient (Xiao and Ju, 2014). Specifically, it changes the market share of each product relative to the outside good, but the relative market share between products does not change.

draws from the distributions of v and y.[16] The simulated market shares are calculated as

$$s_{jmt}^{pred}(p_{mt}, X_{mt}^d, \xi_{mt}, \theta) = \frac{1}{ns}\sum_{i=1}^{ns} \frac{e^{\delta_{jmt}+\mu_{ijmt}} \cdot 1(saving_{imt} \geq p_{jmt})}{1+\sum_{r=1}^{J}[e^{\delta_{rmt}+\mu_{irmt}} \cdot 1(saving_{imt} \geq p_{rmt})]} \tag{9}$$

Next, we combine the simulated market shares (9) with the observed market shares to solve for the mean utility levels $\delta_{mt} = (\delta_{1mt}, ..., \delta_{Jmt})'$. Theoretically, the vector of mean utilities δ_{mt} can be retrieved by equating the estimated market shares with the observed market shares from the data for a given θ_2:

$$s_{mt}^{obs} = s_{mt}^{pred}(p_{mt}, X_{mt}^d, \delta_{mt}; \theta_2) \tag{10}$$

However, analytical solutions for δ_{mt} are not available because the system of equations in equation (10) is highly nonlinear. In practice, it can be solved numerically by using the contraction mapping proposed by Berry et al. (1995) as follows[17]

$$\delta_{mt}^{h+1} = \delta_{mt}^h + \ln s_{mt}^{obs} - \ln s_{mt}^{pred}(p_{mt}, X_{mt}^d, \delta_{mt}^h; \theta_2) \tag{11}$$

until the stopping rule $||\delta_{mt}^h - \delta_{mt}^{h+1}|| \leq \epsilon_{in}$ is satisfied, where ϵ_{in} is the inner-loop tolerance level. In our analysis, we set $\epsilon_{in} = 10^{-14}$.[18] Once we find δ_{mt}, the unobservable attributes ξ_{jmt} can be solved as

$$\xi_{jmt}(p_{mt}, X_{mt}^d, s_{mt}^{obs}, \theta) = \delta_{jmt} - (\ln p_{jmt}, X_{jmt}^d)\theta_1 \tag{12}$$

The parameters θ_1 in equation (12) can be estimated by two-stage least squares (2SLS) using instrumental variables (IVs). The demand unobservable ξ_{jmt} is a function of prices, X_{jmt}^d, the observed market shares, and parameters. The GMM estimator $\hat{\theta}$ solves the prob-

[16]To increase computation efficiency and reduce the simulation error, we use Halton sequences to generate the random draws (see Train (2009) for use of Halton sequences). Our results are based on 300 households in each market. We also checked $ns = 500$. We found that it made little difference.

[17]See Berry et al. (1995) for a proof of convergence.

[18]See Dubé et al. (2012) for a discussion of the importance of a stringent convergence rule. They also provide a new computational algorithm for implementing the estimator in random-coefficient discrete choice model, called mathematical program with equilibrium constraints (MPEC). It converges faster than the algorithm that we use here.

lem:

$$\min_{\theta} Q(\theta) = \min_{\theta}(\xi(\theta)'Z)W(Z'\xi(\theta)) \tag{13}$$

where W is the weighting matrix. The convergence criterion for the GMM is 10^{-8}.

To address the price endogeneity problem, we need a set of exogenous instrumental variables. There are two sets of IVs in our study.

The first set of IVs consists of the exogenous product attributes. The instruments include: the observed product characteristics (i.e., constant term, horsepower, vehicle weight, kilometers driven per Yuan of gasoline, vehicle size, and engine size), the sum of corresponding characteristics of other products offered by that firm (if the firm produces more than one product), and the sum of the same characteristics of vehicles produced by rival firms. Berry et al. (1995) show that the above instrumental variables are valid for cars.

The second set of IVs includes some cost variables as instruments for vehicle prices, i.e., steel prices and labor cost since these are the major inputs in vehicle production.[19]

4 Empirical Results

In this section, we present parameter estimates for the random coefficient discrete choice model. We estimate the model without using the 2010Q4 data and the post-policy data (2011-2012) in Beijing. Then we use the estimates to conduct counterfactual analysis to investigate policy effects.

4.1 Estimation Results

The results of the estimation are presented in Table 2. The first panel of the table provides the estimates of the parameters in the mean utility function defined by equation (5). The parameters in the second panel are the estimates of standard deviations of the taste distribution of each attribute. The third panel provides the estimate of the coefficient of the interaction between $\ln(price)$ and $\ln(income)$.

[19] Steel prices are from China Iron and Steel Association, www.chinaisa.org.cn. We measure labor cost by the annual average salaries in each city and each year. The data comes from the yearbook of each city.

Table 2: Estimation Results for the Model

Variables	Coef.	S.E.
Parameters in the mean utility (θ_1)		
Constant	-4.1054**	2.1023
Ln(price)	-9.0232***	2.4291
Ln(horsepower)	2.7730**	1.1501
Weight	2.5713***	0.9104
Gas expenditure (Yuan/km)	-0.6402***	0.2221
Vehicle size	0.7581***	0.0739
Engine size	0.2135	0.2237
Random coefficients (σ)		
Constant	1.3293	1.2574
Ln(price)	-0.5962***	0.1168
Ln(horsepower)	0.3249***	0.1097
Weight	-0.2223	0.5193
Gas expenditure (Yuan/km)	0.0092	1.0609
Vehicle size	0.0003	0.0749
Engine size	0.0339	0.2371
Interactions with Ln(income) (η)		
Ln(price)	0.5629**	0.2690

Note: The model includes bodystyle fixed effects, firm fixed effects, quarter fixed effects, year fixed effects, and city fixed effects. *** significant at 1%; ** significant at 5%; * significant at 10%.

All coefficients of vehicle attributes in the mean utility function are with the expected signs. The results suggest that households prefer powerful but fuel-efficient cars. Vehicles with larger weight and size are more popular, which is consistent with previous research (Berry et al., 1995; Petrin, 2002; Deng and Ma, 2010; Xiao and Ju, 2014; Li et al., 2015). Moreover, the results also imply that households prefer vehicles with larger engine size. In the Chinese automotive market, engine size is usually correlated with whether a vehicle is high-end or low-end (Deng and Ma, 2010).[20]

In the second panel, the estimates for idiosyncratic tastes over weight, gas expenditure, vehicle size and engine size are insignificant. This implies that households are rather homogeneous in their preferences on these vehicle attributes. This finding coincides with Xiao and Ju (2014). However, households do show variation in their preferences on price and horsepower. This adds to the literature on consumer heterogeneity in preference over vehicles.

The estimate on the interaction between $\ln price$ and $\ln income$ is positive and statistically significant, adding to the literature on household heterogeneity. This suggests that households with higher income are less price sensitive.

4.2 Impact on Fleet Composition

To examine the effects of Beijing's VLS, we conduct a counterfactual experiment where the lottery system was not introduced in Beijing. Then we compare the counterfactual results with the observed outcomes under VLS. Since we estimate the model without using the 2010Q4 data and the post-policy data (2011-2012) in Beijing, we use the estimates in Table 2 to simulate market outcomes under no VLS.

With the estimates, we simulate the demand of each product in Beijing in 2012 under counterfactual scenario. To estimate the impact of Beijing's VLS on fleet composition, we first summarize price, horsepower, and fuel efficiency under the cases with and without VLS. Then we depict car price distribution, horsepower distribution, and fuel efficiency dis-

[20] For example, cars with smaller engine size, such as Alto and Jeely, fall in the low-end category, while cars with larger engine size, such Cherokee and Redflag, belong to high-end and luxurious vehicles. Hence, it is intuitive that consumers like high-end cars.

tribution under these two cases. We compare the distributions under these two scenarios to identify the fleet changes.

Table 3 compares the price, horsepower, and fuel efficiency of the cohort of new passenger vehicles registered in Beijing in 2012 with and without VLS. From Table 3, there are significant differences in price, horsepower, and fuel efficiency. Our results indicate that, under the VLS, the sales-weighted average price in Beijing in 2012 increased in about 62,440 Yuan; a 34.48% increase. We also find that the sales-weighted average horsepower under the lottery was about 12.25% higher than that under counterfactual scenario of no policy. Moreover, the fleet becomes less fuel-efficient. The sales-weighted average fuel efficiency of new vehicles registered under the lottery was 12.85 km/liter, relative to 13.41 km/liter under no policy. These results are consistent with our discussion above: the lottery system shifts the new fleet in Beijing toward high-end and more powerful but less fuel-efficient vehicles.

Table 3: Price, Horsepower, and Fuel Efficiency Summary Statistics in Beijing in 2012

	Without VLS		With VLS		
Variables	Mean	S.D.	Mean	S.D.	Difference
Price (1,000 Yuan)	181.11	171.74	243.55	213.67	62.44***
Horsepower (kw)	100.98	31.30	113.35	37.28	12.37***
Fuel Efficiency(km/L)	13.41	2.09	12.85	2.29	-0.56***

Note: All money is in 2012 RMB Yuan. The mean of price, horsepower, and fuel efficiency are sales-weighted means. The new vehicle sales are 949,950 under counterfactual scenario and 527,183 under observed scenario in 2012. *** significant at 1%; ** significant at 5%; * significant at 10%.

With the derived demand for each product and the total sales, we calculate the cumulative density function (CDF) of car prices, horsepower, and fuel efficiency, and plot their distributions. We depict the price distribution, horsepower distribution, and fuel efficiency distribution in Figure 4, 5, and 6, respectively. As shown in Figure 4, the cumulative distribution of prices under the lottery system lies to the right of that under counterfactual scenario of no VLS. This implies that households would buy more expensive cars under the lottery system. Similarly, Figure 5 and 6 indicate that the cumulative distribution of horsepower shifts to the left and fuel efficiency lie to the right, relative to the counterfactual scenario of no policy. That is, the lottery system increases the sales proportion of more powerful but less fuel-efficient cars.

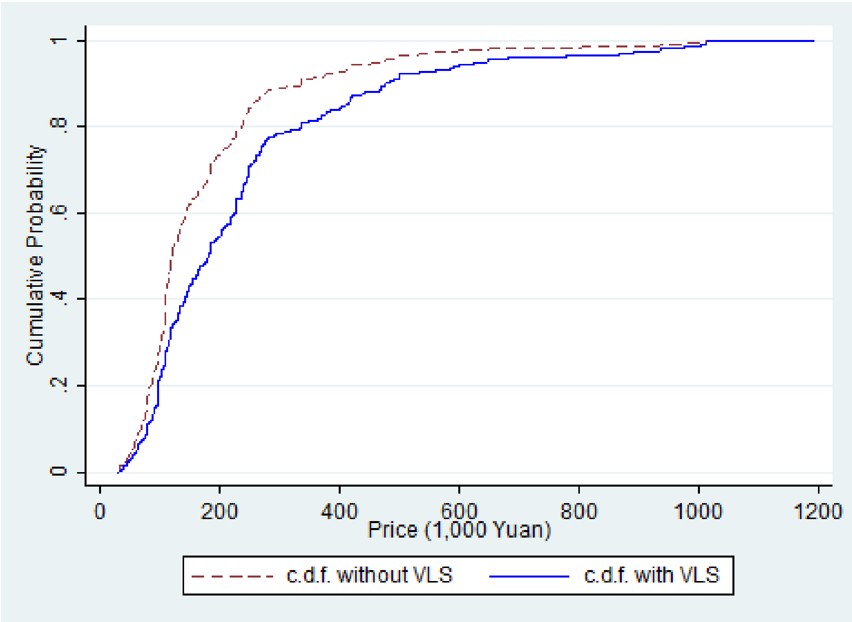

Figure 4: The CDF of Price of New Cars Registered in Beijing in 2012

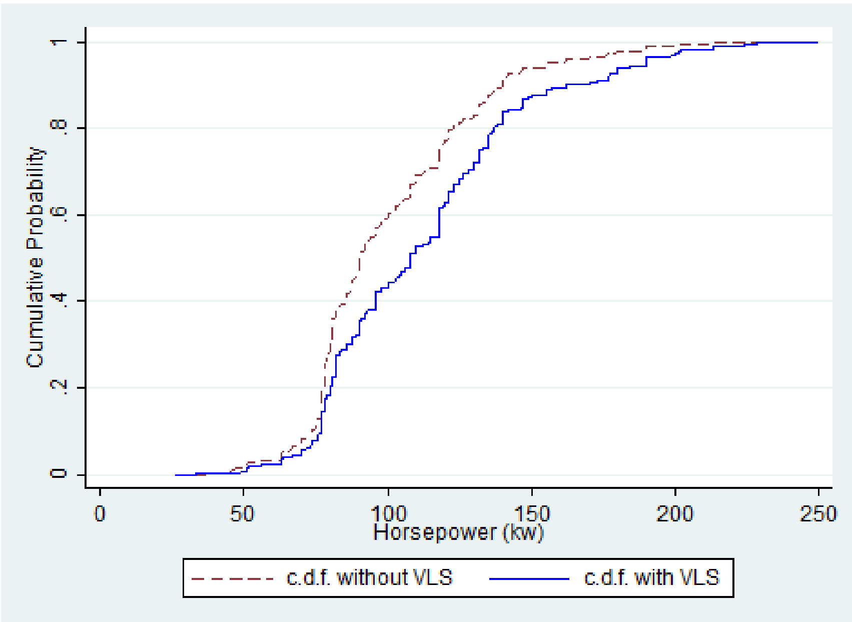

Figure 5: The CDF of Horsepower of New Cars Registered in Beijing in 2012

4.3 Why Does Fleet Composition Change after VLS

Our analysis finds that the fleet of new passenger cars shifts towards high-end, less fuel-efficient vehicles. Yang et al. (2014) also note this tendency because households would

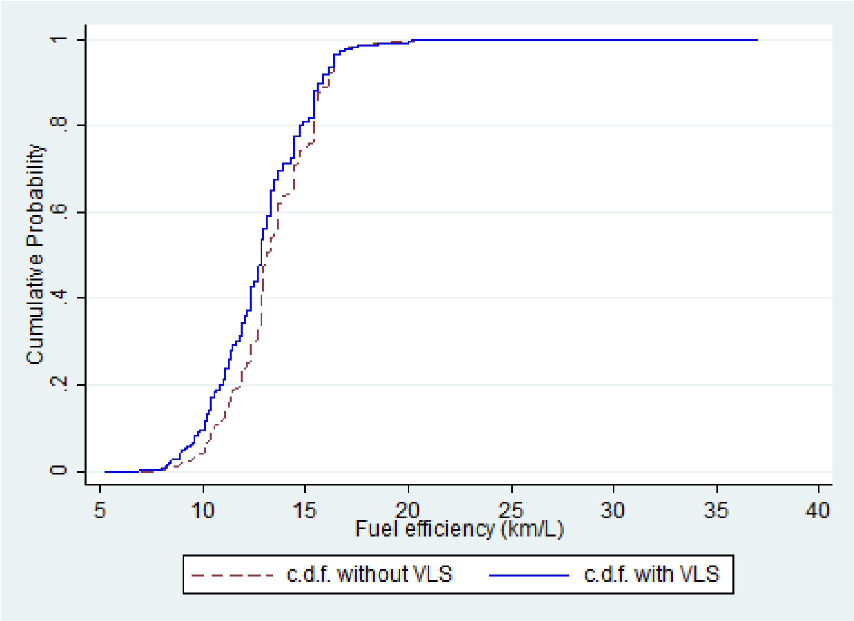

Figure 6: The CDF of Fuel Efficiency of New Cars Registered in Beijing in 2012

spend all the transportation investments on more expensive vehicles due to VLS. However, conditional on entering the lottery, the lottery system randomly assigns licenses to buyers in the lottery pool. Therefore, winning the lottery is not correlated with the characteristics of the households. So the winners' purchase preferences and vehicle choices may not be affected. The purpose of this section is to offer a possible explanation for the result of our analysis from the perspective of how VLS affects households' entering lottery decisions.

Under VLS, a household's decisions can be divided into two stages, as shown in Figure 7. In the stage 1, the household decides whether to enter the lottery. The household only obtain utility $U_{not\ \ enter}$ from consumption of other commodities (i.e., complex good) if he does not enter the lottery. If the household decides to enter the lottery, then we move to stage 2. Upon entering, the household wins the lottery with probability of δ. Once the household wins the lottery, he chooses the most preferred vehicle j, obtaining utility U_j from consuming car and from consumption of a numeraire good. Otherwise, the household only consumes complex good with utility of U_0. We employ backward induction to illustrate the problem.

Stage 2. The household's indirect utility from choosing vehicle j is $U_j = U(y - p_j, \mathbf{q}_j)$, where y is the household income, p_j and $\mathbf{q}_j$ are vehicle j's price and non-price characteristics, respectively. Following Herriges and Kling (1999), we assume additive utilities, i.e.,

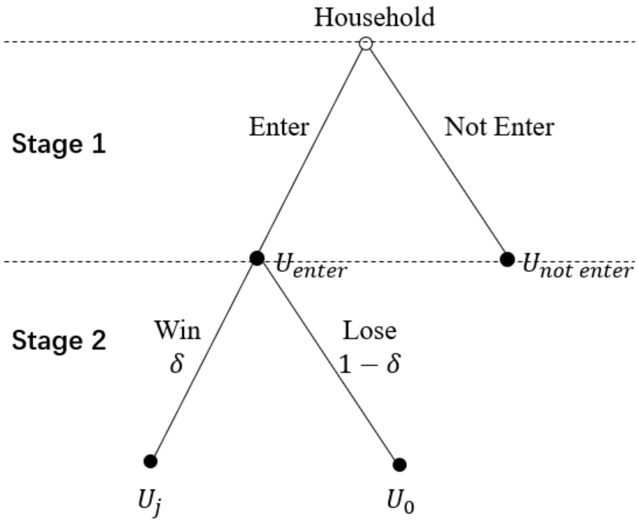

Figure 7: Two Stages of a Household's Decisions under VLS

$U_j = V(y-p_j)+f(\mathbf{q}_j)$. Here, $f(\mathbf{q}_j)$ is the utility from consuming vehicle j. And $V(\cdot)$ denotes the utility from consumption of numeraire good. So the utility function satisfies standard assumptions in the literature: (1) twice continuously differentiable, (2) strictly increasing, i.e., $V'(\cdot) > 0$, (3) strictly concave, i.e., $V''(\cdot) < 0$, and (4) Inada conditions, i.e., $\lim_{x\to 0} V'(x) = \infty$ and $\lim_{x\to\infty} V'(x) = 0$. If the household loses the lottery, the utility is $U_0 = V(y)$. As a result, the expected utility in stage 2 is:

$$EU = \delta U_j + (1-\delta)U_0 = \delta V(y-p_j) + \delta f(\mathbf{q}_j) + (1-\delta)V(y)$$

Stage 1. In this stage, the household decides whether to enter the lottery. If the household does not enter, the indirect utility is defined by $U_{not\ \ enter} = V(y)+\varepsilon_0$. As noted in stage 2, the indirect utility of entering the lottery is specified as $U_{enter} = \delta V(y-p_j) + \delta f(\mathbf{q}_j) + (1-\delta)V(y)+\varepsilon_1$. Here, ε_0 and ε_1 follows i.i.d. type I extreme value distribution. Hence, the conditional probability of entering the lottery can be written as

$$\text{Prob(enter)} = \frac{\exp[\delta V(y-p_j)+\delta f(\mathbf{q}_j)+(1-\delta)V(y)]}{\exp[V(y)]+\exp[\delta V(y-p_j)+\delta f(\mathbf{q}_j)+(1-\delta)V(y)]}$$

Taking derivative with respect to y and rearranging the equation, we obtain

$$\frac{\partial \text{Prob(enter)}}{\partial y} = \text{Prob(enter)} \cdot [1-\text{Prob(enter)}] \cdot \delta \cdot [V'(y-p_j) - V'(y)]$$

Given $V'(\cdot) > 0$, $V''(\cdot) < 0$, and $y - p_j < y$, it implies $V'(y - p_j) - V'(y) > 0$. Therefore, we find $\frac{\partial \text{Prob(enter)}}{\partial y} > 0$, meaning that high income households are more likely to enter the lottery. Although the VLS randomly assigns licenses to buyers in the lottery pool, wealthier consumers enter the lottery due to the policy. Proportion of winners with high income increases. High income household would buy more expensive vehicles and therefore the fleet shifts toward high-end but less fuel-efficient cars. Li et al. (2015) also provide additional evidence to support our illustration. In their stated preference survey conducted in Guangzhou, the average income of lottery participants ranks second, which comes after that of bidding participants.

5 Conclusion

With the rapid growth in vehicle population, problems such as congestion, energy shortages, air pollution and its health consequences have become a major concern in Beijing and other cities worldwide. To control vehicle growth and thereby address related environmental issues, Beijing's municipal government imposed a vehicle quota system and allocated the quota through lottery. In this paper, we investigate the impacts of such novel policy on fleet composition. To do this, we estimate a random coefficient discrete choice model of automotive oligopoly using registration data of new passenger vehicles in Beijing, Nanjing, Shenzhen, and Tianjin. To identify the effects of the lottery, we then conduct counterfactual analysis based on the model estimates.

Our main result suggests vehicle fleet composition changes due to the VLS, shifting it towards less fuel-efficient cars. This change can undermine the potential benefits of the VLS. We further illustrate the underlying mechanism of this finding with a theoretical model. It suggests that households with higher income are more likely to enter the lottery. As a result, the proportion of wealthy households in the pool increases. This drives the demand towards high-end vehicles, since high income household would purchase these cars. Our result would provide the policy market a guideline of what to expect if a similar policy is implemented in other cities.

The VLS in Beijing has been emulated in Guiyang, Guangzhou, Tianjin, Hangzhou, and Shenzhen, and similar programs are being considered for other Chinese cities, such as Chengdu and Wuhan. Our analysis suggests that VLS hinders fleet fuel efficiency due to its impact on fleet composition. As a result, VLS could still be improved by setting detailed quotas for fuel efficiency categories or engine size categories.

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