Effective or Efficient? Effects of Beijing’s Vehicle Lottery System on Fleet Composition and Environment*

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Abstract

To control vehicle growth and air pollution, Beijing’s municipal government imposed a vehicle lottery system in 2011, which randomly allocated a quota of licenses to potential buyers. This paper investigates the effect of this policy on fleet composition, fuel consumption, air pollution, and social welfare. 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 lottery reduced new passenger vehicle

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sales by 50.15%, fuel consumption by 48.69%, and pollutant emissions by 48.69% in 2012. Also, such lottery shifted new auto purchases towards high-end but less fuel efficient vehicles. In our counterfactual analysis, we show that a progressive tax scheme works better than the lottery system at decreasing fuel consumption and air pollution, and leads to a higher fleet fuel efficiency and less welfare loss.

KEYWORDS: Vehicle Lottery System; Fleet Composition; Fuel Consumption; Air Pollution; Welfare Consequences

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

A steady increase in vehicle ownership and usage worldwide has been accompanied by tremendous increase in energy consumption, severe air pollution, and health concerns in many cities around the world, especially in developing countries (Economist Intelligence Unit, 2010; Xiao et al., 2016). Examining the effectiveness of vehicle policies to reduce fuel consumption and air pollution in emerging markets is increasingly important for at least three reasons. First, air pollution is a particularly acute problem in developing countries where it often exceeds the recommended health limit (Alpert et al., 2012; Greenstone and Hanna, 2014; Li, 2015). High air pollution has adverse health consequences, such as cardiopulmonary diseases (EPA, 2004), premature deaths (Cropper, 2010; Chen et al., 2013; Wolff, 2014), and infant mortality (Chay and Greenstone, 2003; Currie and Neidell, 2005). Second, the fluctuation of world oil prices and instability in the Middle East raise concerns about energy security, especially for some developing countries with surging energy demands. The third reason to investigate environmental regulations is that individual countries are responsible to reduce greenhouse gas emission (GHG), with the global increase in GHG emissions been mainly driven by emerging economies, such as China and India.

China offers a fertile ground for exploring the effectiveness of vehicle environmental regulations. First, China is facing very serious air pollution problems, which are particularly serious in big cities, such as Beijing. Twelve of the twenty most polluted cities in the world can be found in China (World Bank, 2007). In addition, motor vehicles, specifically cars, are a major source of air pollution in China's big cities (Ministry of Environmental Protection, 2011; Chen and Zhu, 2013; Viard and Fu, 2015). To control vehicle ownership and usage and to address related environmental problems, both central and local governments have enacted and enforced a wide range of policies, including vehicle consumption taxes, fuel taxes, etc.

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1 In 2013, China crude oil consumption was 10.48 million barrels per day, accounting for about 12% of world crude oil consumption according to United State Energy Information Administration.
2 In 2013, the United State's CO2 emissions increased by 2.5% and the EU28's CO2 emissions decreased by 1.4%, relative to 2012. Other OECD countries also significantly show decreases or minor increases below 2%. In contrast, relative to 2012, CO2 emissions in developing countries mainly increased in 2013, e.g., in China by 4.2%, in India by 4.4%, in Brazil by 6.2% (Netherlands Environmental Assessment Agency, 2014).
3 Zheng and Kahn (2013) provide a comprehensive review on China's urban pollution and governments' policies to address urban pollution externalities. Greenstone and Hanna (2014) demonstrate that ambient particulate matter concentrations in China are seven times the US level.
public transportation subsidies, tightening vehicle emission standards, driving restrictions, vehicle quota systems, and subsidy schemes on new energy vehicles. As a result, investigating the efficacy of such policies in emerging economies, such as China, provides insights on designing environmental regulations to curb fuel consumption and air pollution.

In this paper, we focus on Beijing’s vehicle lottery system (VLS). In 2011, Beijing municipal government imposed a vehicle quota system to control vehicle population growth. Unlike the vehicle license auction system in Shanghai, about 20,000 new licenses are randomly allocated through monthly 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. However, the effectiveness of the VLS has never been fully investigated. It is urgent to empirically quantify its environmental and welfare consequences, since this is a novel policy no other city has used, and thus is being closely observed and adopted by other large cities in the region.

This paper investigates the effects of Beijing’s vehicle lottery system (VLS) on fleet composition, gas consumption, pollutant emissions, and social welfare. To begin with, we construct and estimate a random coefficient discrete choice model developed by Berry et al. (1995) using car registration data for Beijing, and three more cities with similar characteristics that did not implement the VLS, Nanjing, Shenzhen and Tianjin. The model incorporates household preference heterogeneity and unobserved product attributes. To identify the effects of the VLS, we then simulate the outcomes under the counterfactual scenario of no policy and compare them with the observed facts. Moreover, to compare the effectiveness of the VLS with other policies, we conduct another two counterfactual experiments, in which we respectively replace the lottery system with a hypothetical first registration tax and a hypothetical consumption tax.

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4 Those residents who scrap or sell their existing cars do not need to enter the lottery.
5 Guiyang adopted license lotteries in July 2011. Guangzhou, Tianjin, Hangzhou, and Shenzhen implemented a hybrid system combining lotteries and auctions in July 2012, December 2013, March 2014, and December 2014, respectively. Other large Chinese cities (Chengdu, Chongqing, Qingdao, and Wuhan) have considered enacting similar control policies.
6 The first registration tax was introduced in Hong Kong. On the first registration of a motor vehicle, a tax rate proportional to the vehicle class is charged on its taxable value (usually the retail price). In this paper, we revise the tax rates so that new vehicle sales coincide with those under the VLS. Based on the consumption tax in 2008, we construct a hypothetical consumption tax scheme so that it is as effective as the lottery system in controlling for new vehicle sales.
Our study provides interesting findings. First, Beijing’s VLS successfully reduced new car sales by 50.15%, gas consumption by 48.69%, and pollutant emissions by 48.69% in 2012. However, the cost of these benefits is a social welfare loss, implying that such policy is costly. Second, the lottery policy changed the fleet composition. We find that the fleet skewed towards high-end and less fuel efficient vehicles. The empirical findings show that the sales-weighted average price of cars registered in Beijing in 2012 under the lottery system is about 42,430 Yuan (US$6,212) higher than under no policy. The fleet fuel efficiency is 8.09 L/100km under the lottery system, relative to 7.85 L/100km under no policy. Finally, our counterfactual analysis shows that progressive tax policies are as effective as Beijing’s VLS in controlling new vehicle sales but achieve better effects in reducing fuel consumption and air pollution. In our study, fuel consumption (or air pollution) were reduced by 56.67% under the hypothetical first registration tax system, by 55.01% under the hypothetical consumption tax scheme, and but only by 48.69% under the VLS in 2012. In addition, these tax policies result in higher fleet fuel efficiency, which could improve from 8.09 liters/100km under the VLS to 7.36 liters/100km under the hypothetical first registration tax system and 7.48 liters/100km under the hypothetical consumption tax scheme. Moreover, welfare could increase by 69.31 billion Yuan (US$10.14 billion) or 79.83 billion Yuan (US$11.68 billion) in 2012 if Beijing were to replace the VLS with the first registration tax system or the consumption tax scheme, respectively.

**Related literature.** Our paper is related to studies by Xiao and Zhou (2013), Xiao et al. (2016) and Li (2015), who analyze vehicle quota systems in China. Xiao and Zhou (2013) examine the impacts of Shanghai’s vehicle auction system on vehicle control, fleet efficiency, gas consumption and pollutant emissions. Further, Xiao et al. (2016) investigate the influence of the auction system on the market structure in Shanghai. Our work differs in two ways. First, this paper focuses on Beijing’s VLS which is a non-market based mechanism which allocates the quota through lottery, while Shanghai’s vehicle quota system allocates the license plates by auction, in which households with the highest willingness to pay get the quota. Second, we also provide a welfare measure of the performance of the VLS in Beijing. Li (2015) finds that, compared with a uniform price auction, Beijing’s VLS led to a welfare
loss of nearly 58 billion Yuan (about US$ 9.19 billion) in Beijing in 2012. Our paper differs in two respects. First, we mainly focus on the impact of Beijing’s VLS on the automotive fleet’s composition and environment. Our study is the first paper to analyze the fleet composition effect of Beijing’s vehicle lottery system. Second, we also compare the environmental and welfare consequences of the lottery with those of other tax policies, showing that these tax policies are superior to VLS in both environmental benefits and welfare. By comparing our results with Li’s (2015), we find that tax policies work better than a uniform price auction for environmental purpose.

Recently, Yang et al. (2014) use hypothetical Beijing’s gross regional product (GRP) to predict the influence of the lottery system on vehicle growth and hence fuel consumption in 2020. Similarly, Li and Jones (2015) analyze this policy’s effects on vehicle population and CO₂ emissions in 2020 based on hypothetical permanent population and GDP in Beijing. However, this literature does not consider that vehicle demand is mainly driven by household demographics and vehicle attributes, such as household income, vehicle price and performance. Unlike these studies, we derive vehicle demand from household preferences and their choices. Incorporating these features can yield better predictions about the effects of existing policies and generate welfare implications (Chetty, 2015).

Our study also adds to the empirical literature on non-price emission-reduction policies. Most of the literature focuses on fuel tax (Parry and Small, 2005; Fullerton and Gan, 2005; Bento et al., 2009; Xiao and Ju, 2014), consumption tax (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), and Low Emission Zones (Wolff and Perry, 2010; Wolff, 2014). However, few empirical studies to date have compared the effectiveness of market-based and non-market based policies, except Li (2015), who conducts a welfare comparison between Beijing’s lottery system and a uniform

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7 Under a uniform price auction, the government allocates Q licenses among N bidders, each submitting a one-dimensional bid to obtain a license. Upon receiving the list of bids, each of the Q highest bidders receives one license, and each pays a price equal to the highest rejected bid. For instance, consider an auction with 6 consumers and a quota of 3 licenses to allocate, where consumers 1, 2, 3, 4, 5, and 6 submit bids of $10, $9, $8, $7, $6, and $5, respectively. In this setting, the highest rejected bid is $7, entailing that consumers 1, 2, and 3 win a license, each of them paying $7.

8 Berry et al. (1995), Petrin (2002), Xiao and Ju (2014), and Li et al. (2015) prove the importance of these factors in vehicle demand.
Economists have raised concerns over non-market based policies because behavioral responses could mitigate net policy benefits [Davis, 2008; Gibson and Carnovale, 2015]. For example, households could respond to the vehicle lottery policy by concentrating their budget into a single high-end but less fuel efficient car rather than two low-end cars, which lowers fleet fuel efficiency. Therefore, broader comparisons between the lottery system with other policy tools such as taxes have important policy implications. Our paper compares the lottery system with other two tax schemes and finds that a progressive tax system could be a good substitute for Beijing’s VLS.

The rest of the paper is organized as follows. Section 2 briefly reviews China’s automobile industry and Beijing’s VLS, and introduces the data. Section 3 describes the empirical model and the estimation strategies. Section 4 reports our estimation results. Section 5 provides counterfactual analysis. Section 6 concludes.

2 Industry Background, Policy and Data Description

2.1 Industry Background

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%. And the growth rate increased particularly rapidly over the last several years (17% in 2008, 21.76% in 2009, and 24.36% in 2010). With new vehicle sales of 13.65 million and new vehicle production of 13.79 millions in 2009, China surpassed the U.S. market and became the largest auto market in the world in both sales and production.

In 2004, the Chinese government released the new automotive industry development policy. It specifies that the minimum investment size for new entrants is 2 billion Yuan; the ownership of Chinese partners in the joint venture cannot be lower than 50%; and each foreign firm can form joint ventures with at most two Chinese companies. With these barriers, the number of auto makers has been relatively stable since then. In China, the top

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9 The average growth rate of vehicle population in the United States from 2000 to 2009 was 1.19%.
10 In addition, according to China Vehicle Emission Control Annual Report (2010-2013), the percentage of passenger vehicles increased from 8.3% in 1990 to 78% in 2009, 79% in 2010, 80.7% in 2011, and 82.5% in 2012, implying a switch of purchasing from commercial to private purposes.
ten manufacturers of passenger vehicle accounted for 83.3% of sales in 2008 (Xiao and Ju 2014). Among them, joint ventures between local manufacturers and foreign carmakers, such as Shanghai Auto with General Motors and Volkswagen, Beijing Auto with Chrysler and Hyundai, take two thirds of the passenger vehicle market. The rest is taken up by indigenous-brand manufacturers, such Chery and Geely.

2.2 Policy Description

Over the last three decades, China's economy has developed rapidly and household income has grown dramatically, especially in some big cities. In Beijing, gross domestic product (GDP) per capita increased from US $2,915 in 2000 to US $10,910 in 201011 increasing vehicle population from 1.04 million in 2000 to 4.50 million in 2010.

However, this fast growth in vehicle population led to traffic congestion and air pollution. Beijing is often ranked as one of the most congested cities in the world. The average traffic speed on arterial roads during morning peak hours was 20 km/h in 2010, compared with 30 km/h in 2003 (Beijing Transport Research Center 2004-2011). Moreover, Beijing was one of the world's most air polluted cities in 2013.12 According to the China's Vehicle Emission Control Annual Report 2010, emissions from vehicles is the main source of air pollution in China's major cities. From 2010, Beijing's average daily concentration of PM2.5 frequently reaches over 250 µg/m³, which is much higher than the recommended daily level of 25 µg/m³ by the World Health Organization (2006).13

To reduce vehicle congestion and air pollution, Beijing's municipal government has adopted some policies, such as driving restrictions from July 20, 2008. Viard and Fu (2015) found that the restrictions reduced particulate matter pollution by 7%-19% in the short run. However, some studies indicate that permanent driving restrictions do not successfully reduce air pollution or traffic congestion (Davis 2008; de Grange and Troncoso 2011), because households circumvent the restriction by buying second cars.

11 Beijing Yearbook, 2013.
13 Air pollution is also linked to some extreme conditions, such as cardiopulmonary diseases, respiratory infections, lung cancer (EPA 2004), infant mortality (Chay and Greenstone 2003), and childhood asthma (Neidell 2004).
To further ease traffic congestion and improve air quality, Beijing municipal government 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) for 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[^1^] or apply at a walk-in service center without cost.

Beijing’s Municipal Commission of Transport publishes the lottery results on the lottery system's website. Each winner can download a certificate online or pick up it at a walk-in service center. The certificate allows the quota holder to purchase a license plate and register a vehicle. The 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 and driving in Beijing. Out-of-state vehicles need to obtain temporary driving permits to enter the 5th ring road[^15^]. Moreover, these

[^15]: The 5th ring road is about 98.58 km in length and the area within it is about 700 km².
vehicles are banned to travel within the 5th ring road (inclusively) during peak hours.

2.3 Data

2.3.1 Data Description

This paper focuses on the effects of vehicle lottery policy in Beijing based on data from 2009 to 2012. To control the effects of other factors, such as trends and tax deduction, we choose Nanjing, Shenzhen, and Tianjin to facilitate identification.\textsuperscript{16} These cities are the largest cities and they did not have policies on vehicle ownership or vehicle usage during our sample period. The characteristics of these four cities are shown in Appendix Table\textsuperscript{17}. Appendix Table\textsuperscript{17} shows that Shenzhen has the highest average household income, GDP per capita, and average consumption expenditure per capita, while Tianjin has the lowest. Beijing approximates Nanjing in these dimensions. Generally, these cities are similar in average household income, GDP per capita, and average consumption expenditure per capita. In addition,\textsuperscript{18} Li (2015) proves common trend of vehicle sales in Tianjin, Nanjing, and Beijing.

There are two main data sources for this study. The first data set contains monthly new passenger vehicle registration information in each city from January 2009 to December 2012, including manufacturer, brand, model year, model, engine displacement, car type, and quantity.\textsuperscript{18} In this paper, we focus on passenger vehicles and a product is defined as a unique combination of the model year, manufacturer, brand, model, engine displacement, and car type. For example, 2009 Beijing Benz C200 1.8T Sedan, 2010 Beijing Benz C200 1.8T Sedan, and 2009 Beijing Benz C230 2.5L Sedan are different products. In addition, we define a market as a city-year-quarter combination. For example, Beijing-2010-Q1 is a different market from Beijing-2010-Q2. Therefore, we aggregate the monthly data into quarterly lev-

\textsuperscript{16} 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. From 2011, these tax deductions were canceled.

\textsuperscript{17} In mainland China, Beijing is the second largest city in population, Shenzhen is the fourth, Tianjin is the fifth, and Nanjing is the twelfth. Source: http://www.worldatlas.com/citypops.htm.

\textsuperscript{18} In China, vehicle registration data are not released to the public. We obtain the data from Dalian Wismar Information Co., Ltd. The data provider required us not to release the data to protect his proprietary information. We adopt the term “sales” to substitute for “the number of newly registered passenger vehicles”. The number of registered vehicles in a city is different from the vehicle sales in that city. For example, consumers in nearby cities may buy vehicles in Beijing and register cars in their own cities. However, vehicle sales in this paper refers in particular to the number of registered vehicles.
els and use the total sales and average quarterly prices for each quarter to measure their sales and prices. There are 41,006 observations in our sample.

Figure 1: New Vehicle Quarterly Sales in Beijing, Nanjing, Shenzhen, and Tianjin

Figure 1 plots quarterly sales of new vehicles in Beijing, Nanjing, Shenzhen, and Tianjin. Figure 1 shows that the lines track each other well before 2011, reflecting a common trend across these cities. In addition, we can find that there was strong seasonal effects, whereby sales increase at the end of each year. A possible explanation is that people receive their year-end bonuses, enabling them to purchase big-items such as cars. Finally, new vehicle sales in Beijing increase dramatically in the fourth quarter of 2010 and then decrease sharply in the first quarter of 2011. Since Beijing municipal government issued a plan to control vehicle registrations on December 13, 2010, consumers may have been afraid to not purchase vehicles after the quota, moving their purchases into December 2010. To avoid this anticipation effect, we drop the last quarter in 2010 and the first quarter in 2011 across all cities in our study.\footnote{When the policy was announced, it was possible that consumers in other cities were affected, anticipating that similar policies will be applied in their own cities. As a consequence, we drop the last quarter in 2010 and the first quarter in 2011 in control cities in our main analysis. As a robustness check, we also estimate the model without dropping the data during this period in control cities in section 4.2.}

To complete the data set, we collect vehicle attribute data from the website auto.sohu.com and Car Market Guide. Transaction prices are not available. Following the auto demand literature, we use Manufacturer Suggested Retail Prices (MSRP) in this study. Vehicle prices are computed based on MSRP and the sales tax. Li et al. (2015) argue that, unlike U.S. auto
market, promotions in China’s auto markets are not frequent and, hence, MSRP can be a good proxy for retail prices. The sales tax is 10% in all of these cities except in 2009 and 2010. In 2009 and 2010, the sales tax was reduced to 5 and 7.5 percent for vehicles with engine displacement below 1.6 liter, respectively. From 2011, these tax deductions were cancelled. The data set also includes horsepower (in kilowatts), car weight (in 1,000 kilograms), vehicle size (in m$^2$), fuel efficiency (in Liters/100km), and engine displacement (in Liters). In addition, we also obtain gasoline prices from National Development and Reform Commission of China to construct a fuel economy variable, i.e., kilometers driven for 1 RMB Yuan’s gasoline. All prices are in 2009 RMB Yuan. We use the Consumer Price Index to deflate.

Table 1 provides the summary statistics of our sample. Both quarterly sales and prices have large variations. The most popular passenger car has a quarter sale of 6,620 units whereas the least popular car had only one sale. The average price is 188,570 Yuan, ranging from 26,040 to 11,243,500 Yuan. The average price is higher than the average household income. Horsepower and engine displacement are correlated with vehicle performance. The most powerful vehicle has a horsepower of 515 kw, while the least has a horsepower of 26.5 kw. Engine displacement varies from 0.8L to 6.8L. Vehicle weight and vehicle size are indicators of comfort and safety (Winston and Yan, 2016). The lightest car weighs 650 kg, whereas the heaviest one weighs 2,950 kg. The largest vehicle is 12.51 m$^2$, while the smallest one is 4.20 m$^2$. Fuel efficiency and fuel economy are used to measure vehicle fuel consumption performance. The least fuel efficient vehicle consumes 26 liters of gasoline for a 100 kilometers’ drive, while the most fuel efficient one consumes only 2.7 liters.

The second data set is the household income distribution in each city and year, which is constructed through Chinese Household Income Survey (2007) and annual statistical yearbooks of each city. Following Li et al. (2015), we use their method to construct household income distribution from 2009 to 2012 in each city. First, we obtain average household income for five income levels or seven income levels from the yearbooks. Second, we divide

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20 Fuel efficiency data are obtained from Ministry of Industry and Information Technology of China. Consumer Price index are from National Bureau of Statistics of the People’s Republic of China.
22 In some cities, households are divided into five income levels: low income households (first quintile),
Table 1: Summary Statistics of Vehicle Data 2009-2012

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quarterly sales by product</td>
<td>110.49</td>
<td>292.20</td>
<td>1</td>
<td>6,620</td>
</tr>
<tr>
<td>Price (1,000 Yuan)</td>
<td>188.57</td>
<td>225.14</td>
<td>26.04</td>
<td>11,243.50</td>
</tr>
<tr>
<td>Weight (1,000 kg)</td>
<td>1.37</td>
<td>0.29</td>
<td>0.65</td>
<td>2.95</td>
</tr>
<tr>
<td>Horsepower (kw)</td>
<td>101.88</td>
<td>37.53</td>
<td>26.50</td>
<td>515.00</td>
</tr>
<tr>
<td>Vehicle size (m$^2$)</td>
<td>8.03</td>
<td>0.91</td>
<td>4.20</td>
<td>12.51</td>
</tr>
<tr>
<td>Fuel efficiency (L/100km)</td>
<td>7.94</td>
<td>1.50</td>
<td>2.70</td>
<td>26.00</td>
</tr>
<tr>
<td>Fuel economy (km/Yuan)</td>
<td>2.17</td>
<td>0.40</td>
<td>0.59</td>
<td>7.19</td>
</tr>
<tr>
<td>Engine displacement (L)</td>
<td>1.86</td>
<td>0.56</td>
<td>0.80</td>
<td>6.80</td>
</tr>
</tbody>
</table>

Note: All money is in 2009 RMB Yuan. The number of observations is 41,006. The mean of price, weight, horsepower, vehicle size, fuel efficiency, fuel economy, and displacement are sales-weighted means.

5,000 observations in the survey into five income levels or seven income levels. Finally, we adjust the household income in the survey proportionally and separately for each income level. After adjustment, the interpolated income distribution from the survey in a given year and city is consistent with income statistics from the yearbook of that city and year. Following the literature, we assume that the logarithm of household income follows the normal distribution. Since Chinese Household Income Survey (2007) is a national survey, the derived household income distributions may be different from income distributions of vehicle buyers. Hence, we use a survey conducted among vehicle owners in Beijing by the Guanghua School of Management at Beijing University in 2005 as a robustness check.\(^{24}\)

### 2.3.2 Stylized Facts

The above summary statistics do not show the changes of vehicle characteristics across the cities over time. Figure 2 to Figure 4 display the quarterly average prices, horsepower, and fuel efficiency, respectively. As shown in Figure 2 before 2011, Shenzhen has the highest sales-weighted average price, followed by Beijing, while Tianjin has the lowest.\(^{25}\) However, medium-low income households (second quintile), medium income households (third quintile), medium-high income households (fourth quintile), and high income households (fifth quintile). Some other cities use seven income levels: lowest income households (first decile), low income households (second decile), medium-low income households (second decile), medium income households (third decile), medium-high income households (fourth decile), high income households (ninth decile), and highest income households (tenth decile).

\(^{24}\) Summary statistics of this survey can be found in study by Xiao and Ju (2014).\(^{25}\) In particular, the sales-weighted average price of Beijing is about 8.23\% lower than that of Shenzhen, 13.59\% higher than that of Nanjing, and 39.21\% higher than that of Tianjin.

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\(^{24}\) Summary statistics of this survey can be found in study by Xiao and Ju (2014).

\(^{25}\) In particular, the sales-weighted average price of Beijing is about 8.23\% lower than that of Shenzhen, 13.59\% higher than that of Nanjing, and 39.21\% higher than that of Tianjin.
the sales-weighted average price in Beijing increases from 184,840 Yuan before January 2011 to 240,410 Yuan after January 2011, representing a 30.06% 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 13.02% higher than that of Shenzhen, 36.02% higher than that of Nanjing, and 66.66% higher than that of Tianjin. From Figure 3 and 4 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 make buyers switch to high-end, more powerful, but less fuel efficient cars. Moreover, Figure 2 to 4 indicate that the sales-weighted average price, horsepower, and fuel efficiency are not in steady state in 2011. So we focus on 2012 in our counterfactual analysis.

![Figure 2: Quarterly Sales-weighted Average Prices (1,000 Yuan) 2009-2012 in Four Cities](image)

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, fuel consumption, and pollutant emissions in Beijing.
3 Empirical Model and Estimation

3.1 Utility Function Specification

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

In our analysis, a market $t$ is defined as a city-year-quarter combination, such as Beijing-2010-Q1. In a market, a product $j$ is defined as a unique combination of the model year,
manufacturer, brand, model, engine displacement, and car type, for example, 2009 Beijing Benz C200 1.8T Sedan. Consider a set of markets, $t = 1, \ldots, T$, where a set of products, $j = 0, 1, \ldots, J$, is available for each market. We use 0 to denote the outside good (i.e., the choice of purchasing an electric vehicle or not buying a new vehicle). Let $i$ denote a household. The utility from outside good is normalized to $\varepsilon_{i0t}$, which follows i.i.d. type I extreme value distribution, as in Berry et al. (1995) and Li (2015). In market $t$, the indirect utility of household $i$ when purchasing product $j$ is given by

$$
u_{ijt} = x_{jt} \beta_i + \alpha_i \ln p_{jt} + \lambda_{type} d_{type} j + \lambda_{firm} d_{firm} j + \lambda_{quarter} d_{quarter} + \lambda_{year} d_{year} + \lambda_{city} d_{city} + \xi_{jt} + \varepsilon_{ijt}$$

(1)

where $x_{jt}$ is a vector of product $j$’s observed characteristics in market $t$, including a constant term, logarithm of horsepower, vehicle weight, kilometers driven per Yuan of gasoline (fuel economy), and engine displacement. $p_{jt}$ is the price of product $j$ in market $t$. $d_{type} j$ is a vector of car type dummy variables (e.g., sedan, SUV, MPV, station wagon, and coupe) and $d_{firm} j$ is a vector of firm dummy variables, capturing households’ intrinsic preference for vehicle types and products from different firms. The model also includes quarter dummies, year dummies, and city dummies to capture market-specific effects, such as seasonal effects and city fixed effects. $\xi_{jt}$ is the unobserved (to researchers) characteristics of product $j$ in market $t$, such as product quality. $\varepsilon_{ijt}$ 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 are less price sensitive. Household heterogeneity is captured by random coefficients $\alpha_i$ and $\beta_i$. In particular, $\alpha_i$ is household $i$’s marginal utility from income and it is given by

$$\alpha_i = \bar{\alpha} + \eta \ln y_i + \sigma_p v_i^p$$

(2)

where $y_i$ is household income, and $v_i^p$ is unobserved household characteristics that affect

\[26\] The electric vehicles accounted for only 0.044% of all newly registered passenger vehicles. Customers of electric vehicle don’t need to enter the lottery to get a license.
household preferences and follow standard normal distribution. Since households with a higher income \( y_i \) tend to be less price sensitive, we expect \( \eta \) to be positive.

Similarly, \( \beta_{ik} \) measures household-specific taste on vehicle characteristic \( x_{jtk} \), which is the \( k \)th attribute of product \( j \). Specifically, \( \beta_{ik} \) is defined by

\[
\beta_{ik} = \bar{\beta}_k + \sigma_k v_i^k
\]

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.

After combining equations (1), (2), and (3), we obtain

\[
u_{ij} = K \sum_{k=1}^{K} x_{jk} \bar{\beta}_k + \bar{\alpha} \ln p_j + \lambda_{type} \text{type}_j + \lambda_{firm} m_j + \lambda_{quarter} + \lambda_{year} + \lambda_{city} + \xi_j + \sum_{k=1}^{K} \sigma_k x_{jk} v_i^k + (\eta \ln y_i + \sigma_p v_i^p) \ln p_j + \epsilon_{ij}
\]

where, for compactness, we suppress the market index \( t \). As in [Berry et al., 1995], the above utility function can be decomposed into a mean utility

\[
\delta_j = \sum_{k=1}^{K} x_{jk} \bar{\beta}_k + \bar{\alpha} \ln p_j + \lambda_{type} \text{type}_j + \lambda_{firm} m_j + \lambda_{quarter} + \lambda_{year} + \lambda_{city} + \xi_j
\]

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

\[
\mu_{ij} = \sum_{k=1}^{K} \sigma_k x_{jk} v_i^k + (\eta \ln y_i + \sigma_p v_i^p) \ln p_j
\]

and a random taste shock \( \epsilon_{ij} \).

### 3.2 Choice Probability and Aggregate Demand

Household chooses the product that maximizes his utility. Given that \( \epsilon_{i0t} \) and \( \epsilon_{ijt} \) follow the i.i.d. type I extreme value distribution, the probability of household \( i \) to purchase product \( j \)
in market $t$ is
\[
    s_{ijt}(p_t, X^d_t, \xi_t, \theta|v_t, y_t) = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{m=1}^J \exp(\delta_{mt} + \mu_{imt})}
\]
(7)

where $p_t = (p_{1t}, \ldots, p_{Jt})'$ and $X^d_t$ includes $x_{jt}$, car type dummies, firm dummies, quarter dummies, year dummies, and city dummies of the products. $\theta$ are the model parameters, where $\theta_1 = (\tilde{\alpha}, \tilde{\beta}, \lambda)'$, $\theta_2 = (\sigma, \eta)'$, and $\theta = (\theta_1, \theta_2)'$. Correspondingly, the market share for product $j$ in market $t$ is
\[
    s_{jt}(p_t, X^d_t, \xi_t, \theta) = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{m=1}^J \exp(\delta_{mt} + \mu_{imt})} dP(y) dP(v)
\]
(8)

where $P(\cdot)$ denotes population distribution functions.

If $N_t$ is the market size in market $t$, the demand for product $j$ is $N_t s_{jt}(p_t, X^d_t, \xi_t, \theta)$. 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.

### 3.3 Identification and Estimation

After the idiosyncratic error term $\varepsilon_{ijt}$ is integrated out analytically, the econometric error term will be the unobserved product characteristics, $\xi_{jt}$, 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
\[
    E(\xi_{jt}|z_{jt}) = 0
\]
(9)

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

To derive $\xi_{jt}$, we first need to estimate market shares. While the market share in equation (8) does not have a closed form, it can be evaluated by Monte Carlo simulation with $ns$ draws.
from the distributions of \( v \) and \( y \). The simulated market shares are calculated as

\[
s_{jt}^{\text{pred}}(p_t, X^d_t, \xi_t, \theta) = \frac{1}{ns} \sum_{i=1}^{ns} \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{m=1}^{J} \exp(\delta_{mt} + \mu_{imt})}
\] (10)

Next, we combine the simulated market shares (10) with the observed market shares to solve for the mean utility levels \( \delta_t = (\delta_{1t}, ..., \delta_{Jt})' \). Theoretically, the vector of mean utilities \( \delta_t \) can be retrieved by equating the estimated market shares with the observed market shares from the data for a given \( \theta_2 \):

\[
s_{t}^{\text{obs}} = s_{t}^{\text{pred}}(p_t, X^d_t, \delta_t; \theta_2)
\] (11)

However, analytical solutions for \( \delta_t \) are not available because the system of equations in equation (11) is highly nonlinear. In practice, it can be solved numerically by using the contraction mapping proposed by Berry et al. (1995) as follows:

\[
\delta_{h+1} = \delta_{h} + \ln s_{t}^{\text{obs}} - \ln s_{t}^{\text{pred}}(p_t, X^d_t, \delta_{h}; \theta_2)
\] (12)

until the stopping rule \( ||\xi_t^h - \xi_t^{h+1}|| \leq \epsilon_{in} \) is satisfied, where \( \epsilon_{in} \) is the inner-loop tolerance level. In our analysis, we set \( \epsilon_{in} = 10^{-14} \). Once we find \( \delta_t \), the unobservable attributes \( \xi_{jt} \) can be solved as

\[
\xi_{jt}(p_t, X^d_t, s_{t}^{\text{obs}}, \theta) = \delta_{jt} - (\ln p_{jt}, X^d_{jt})\theta_1
\] (13)

The parameters \( \theta_1 \) in equation (13) can be estimated by two-stage least squares (2SLS) using instrumental variables (IVs). The demand unobservable \( \xi_{jt} \) is a function of prices, \( X^d_{jt} \), the observed market shares, and parameters. The GMM estimator \( \hat{\theta} \) solves the problem:

\[
\min_{\hat{\theta}} Q(\theta) = \min_{\theta} (\xi(\theta)'Z) W (Z'\xi(\theta))
\] (14)

---

27 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 all based on 150 households in each market. We also checked \( ns = 250 \) using the benchmark specification. We found that it made little difference.

28 See Berry et al. (1995) for a proof of convergence.

29 See Dubé et al. (2012) for the discussion of the importance of a stringent convergence rule. They also provide a new computational algorithm for implementing the BLP estimator, called mathematical program with equilibrium constraints (MPEC). It converges faster than the algorithm that we used here.
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. Following the literature, we assume that the unobserved product attributes are mean independent of observed product characteristics. Based on this assumption, we use three sets of instrumental variables in our analysis: the observed product characteristics (i.e., constant term, horsepower, vehicle weight, kilometers driven per Yuan of gasoline, and engine displacement), 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 products produced by rival firms. [Berry et al. (1995) and Nevo (2000)] show that the above instrumental variables are valid for cars and cereals, respectively. We also evaluate the strength of the instruments and the instrument $F$-statistic in our study is large, with a $p$-value almost 0. So the instruments are strong.

4 Estimation Results

In this section, we first present parameter estimates for the random coefficient discrete choice model. In the benchmark specification, we estimate the model without using the data from the fourth quarter in 2010 to the first quarter in 2011 across four cities and the post-policy data in Beijing (2011-2012). We also report estimation results from alternative specifications.

4.1 Parameter Estimates from the Structural Demand Model

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 $\ln income$.

In the benchmark specification, all coefficients of vehicle attributes in the mean utility function are with the expected signs. The results suggest that households prefer powerful
### Table 2: Estimation Results for the Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Benchmark</th>
<th>S.E.</th>
<th>Alternative 1</th>
<th>S.E.</th>
<th>Alternative 2</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Parameters in the mean utility ($\theta_1$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-7.4147***</td>
<td>2.7315</td>
<td>-7.3137***</td>
<td>1.1184</td>
<td>-6.6066***</td>
<td>1.3264</td>
</tr>
<tr>
<td>Ln(price)</td>
<td>-10.2256***</td>
<td>1.7085</td>
<td>-10.3526***</td>
<td>1.6944</td>
<td>-10.5855***</td>
<td>2.8825</td>
</tr>
<tr>
<td>Ln(horsepower)</td>
<td>5.0841**</td>
<td>2.1023</td>
<td>4.7895***</td>
<td>1.5699</td>
<td>4.5350**</td>
<td>1.8458</td>
</tr>
<tr>
<td>Weight</td>
<td>1.8792</td>
<td>1.5866</td>
<td>1.8727</td>
<td>1.3649</td>
<td>2.6624</td>
<td>2.2185</td>
</tr>
<tr>
<td>Fuel economy (km/Yuan)</td>
<td>0.1148</td>
<td>0.4457</td>
<td>0.3219</td>
<td>0.4399</td>
<td>0.1674</td>
<td>1.1974</td>
</tr>
<tr>
<td>Vehicle size</td>
<td>1.0582***</td>
<td>0.1185</td>
<td>1.0319***</td>
<td>0.1204</td>
<td>1.0476***</td>
<td>0.1465</td>
</tr>
<tr>
<td>Displacement</td>
<td>0.6576</td>
<td>0.4853</td>
<td>0.6568**</td>
<td>0.3279</td>
<td>0.6956**</td>
<td>0.2728</td>
</tr>
<tr>
<td><strong>Random coefficients ($\sigma$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.6035</td>
<td>3.2093</td>
<td>-0.0614</td>
<td>0.9824</td>
<td>-0.1223</td>
<td>1.2873</td>
</tr>
<tr>
<td>Ln(price)</td>
<td>0.3403</td>
<td>0.3077</td>
<td>0.3665</td>
<td>0.3046</td>
<td>0.3828***</td>
<td>0.1184</td>
</tr>
<tr>
<td>Ln(horsepower)</td>
<td>0.4893</td>
<td>0.7227</td>
<td>0.5354***</td>
<td>0.1753</td>
<td>0.7461***</td>
<td>0.1517</td>
</tr>
<tr>
<td>Weight</td>
<td>1.0075*</td>
<td>0.5277</td>
<td>1.0043**</td>
<td>0.4463</td>
<td>0.6876</td>
<td>1.0026</td>
</tr>
<tr>
<td>Fuel economy (km/Yuan)</td>
<td>0.5178**</td>
<td>0.1969</td>
<td>0.3773</td>
<td>0.3307</td>
<td>0.5555</td>
<td>0.8956</td>
</tr>
<tr>
<td>Vehicle size</td>
<td>0.0035</td>
<td>0.1234</td>
<td>0.0007</td>
<td>0.0609</td>
<td>0.0679</td>
<td>0.0966</td>
</tr>
<tr>
<td>Displacement</td>
<td>-0.0056</td>
<td>0.9354</td>
<td>0.0023</td>
<td>0.3151</td>
<td>0.0168</td>
<td>0.3821</td>
</tr>
<tr>
<td><strong>Interactions with Ln(income) ($\eta$)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(price)</td>
<td>0.3141**</td>
<td>0.1488</td>
<td>0.3032**</td>
<td>0.1360</td>
<td>0.3446***</td>
<td>0.1235</td>
</tr>
</tbody>
</table>

Note: The benchmark model is the preferred model. Alternative specification 1 uses household income distributions derived from a survey conducted among vehicle owners by Beijing University. Alternative specification 2 includes the data from the fourth quarter in 2010 to the first quarter in 2011 in Nanjing, Shenzhen, and Tianjin. All specifications include car type fixed effects, firm fixed effects, quarter fixed effects, year fixed effects, and city fixed effects. *** significant at 1%; ** significant at 5%; * significant at 10%.
but fuel efficient cars. Vehicles with larger weight and size are more popular, because they are more comfortable and safer. Our findings are consistent with most 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 displacement. In the Chinese automotive market, engine displacement is usually correlated with whether a vehicle is high-end or low-end (Deng and Ma, 2010). The estimates of vehicle weight, fuel economy and engine displacement are not significant in our benchmark specification.

In the second panel, the estimates for idiosyncratic tastes over price, horsepower, vehicle size and engine displacement 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 vehicle weight and fuel economy. This adds to the literature on consumer heterogeneity in preference over vehicles.

The coefficient on $\ln price$ is negative and significantly different from zero. In addition, the estimate for the standard deviation on the tastes for $\ln price$ is not significant. These results indicate that consumers’ preference on vehicle prices is relatively homogeneous and that households dislike high vehicle prices. 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.

With the estimated parameters, we compute price elasticity for each product. The average own-price elasticity is -8.43. The average own-price elasticity is smaller in magnitude than that obtained by Deng and Ma (2010) which is -9.2. The difference can be explained by the increase in household income that occurred from Deng and Ma’s study, which used 1995-2011 data, to our study, using 2009-2012 data. As household income grows, it is reasonable that consumers are less price sensitive to vehicle price changes than before.

\[ \text{For example, cars with smaller displacement, such as Alto and Jeely, fall in the low-end category, while cars with larger engine displacement, such Cherokee and Redflag, belong to high-end and luxurious vehicles. Hence, it is intuitive that consumers like high-end cars.} \]
4.2 Robustness Checks

To verify the sensitivity of our results to other specifications, we perform several robustness checks to our empirical analysis. Table 2 presents the estimation results of alternative specifications 1 and 2.

**Household income.** In our benchmark specification, the household income distributions are derived from Chinese Household Income Survey (2007), which is a national representative survey. Hence, the derived household income distributions may be different from the income distributions of vehicle buyers. For example, the average monthly household income is 4,395 Yuan in Beijing 2005, while the average household income of vehicle owners is 8,300 Yuan per month (Xiao and Ju, 2014). In alternative 1, we use data from a survey conducted among vehicle owners in Beijing by Beijing University in 2005 to derive the household income distributions. Generally, the coefficients remain similar to those in the benchmark specification. The average own-price elasticity is -8.20, which is about 2.73% smaller than that from the benchmark specification in magnitude. Since the average household income of vehicle owners is higher than that of the masses, the results suggest that higher income reduces price sensitivity. As shown in Table 2, the estimate of engine displacement becomes significant, implying that high income enables households to purchase high-end cars.

**Announcement effect.** To avoid the announcement effect of the policy on the control cities, the benchmark specification dropped the data from the fourth quarter in 2010 to the first quarter in 2011 across the control cities. Alternative specification 2 includes these data. Compared with the benchmark model, the coefficient of engine displacement becomes significant and households show variation in tastes for vehicle prices and horsepower. These results may be caused by the announcement effect of the policy. As the policy was announced in Beijing, it could cause panic among households in other cities, who advanced their future purchases. As a consequence, there are two groups of buyers in the market. One contains those who will buy cars even if Beijing did not implemented VLS. The other group contains buyers who enter the market due to Beijing’s VLS. Since consumers in different groups may have different characteristics, we expect a change in consumer’s preference...
heterogeneity.

### 4.3 Impact on New Vehicle Registration

In this subsection, we examine the effect of Beijing's VLS on new vehicle registration in Beijing. With the estimates under benchmark specification, we simulate the quarterly number of newly registered passenger vehicles for each product in Beijing under counterfactual scenario (I) of no policy. As shown in Table 3, the counterfactual number is 213,638 in the fourth quarter of 2010, whereas the observed number is 257,489. This increase could be mainly caused by panic buying. With the announcement of license plate restriction in Beijing, consumers brought forward their demand for vehicles. Moreover, the new registrations under counterfactual scenario (I) are 757,042 and 1,066,551 in 2011 and 2012, respectively. Compared with observed registrations in 2011 and 2012 under the policy, the lottery reduced new vehicle registrations in Beijing by 54.84% in 2011 and 50.15% in 2012. This suggests that the policy successfully controlled vehicle growth in Beijing.

<table>
<thead>
<tr>
<th>Year and quarter</th>
<th>Observed (with vehicle lottery system)</th>
<th>Counterfactual scenario (I) (without lottery system)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>548,557</td>
<td>548,557</td>
</tr>
<tr>
<td>2010Q1-2010Q3</td>
<td>501,814</td>
<td>501,814</td>
</tr>
<tr>
<td>2010Q4</td>
<td>257,489</td>
<td>213,638</td>
</tr>
<tr>
<td>2011</td>
<td>341,917</td>
<td>757,042</td>
</tr>
<tr>
<td>2012</td>
<td>531,639</td>
<td>1,066,551</td>
</tr>
</tbody>
</table>

Note: The counterfactual outcome is based on benchmark specification.

Our estimates are close to those obtained by Li (2015), where he finds the policy reduced sales by 57% and 54% in 2011 and 2012, respectively. Relative to Li’s (2015) study, the estimated percentage changes in sales were about 2.16 (3.85) lower in 2011 (2012) due to VLS in our study, respectively. The differences could be attributed to the following reason. He uses vehicle sales in his analysis, whereas we use vehicle registration data in this paper. Usually, the number of vehicle sold in a city is not equal to the number of vehicle registered. For

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example, given the abundance of dealerships in Beijing, consumers in nearby cities might buy cars in Beijing and register the vehicles in their cities. Since the VLS only applied to these vehicles registered in Beijing, it is more reasonable to exclude those vehicles sold in Beijing but registered in other cities.

5 Counterfactual Analysis

The purpose of this section is to evaluate the effects of Beijing’s VLS on fleet composition, fuel consumption, and pollutant emissions. Moreover, we compare welfare consequences of vehicle lottery system with other tax-based policies. To examine the effects of the lottery system, we use the estimates under benchmark specification to simulate market outcomes under counterfactual scenario (I) of no policy and compare the results with observed outcomes under the lottery system. Scenario (I) will be used as contrast.

Although vehicle lottery can effectively control vehicle population and reduce gas consumption and air pollution in Beijing, it has been subject to criticism. In a lottery system, the permits to purchase vehicles are distributed randomly. Those without the highest willingness to pay may get the cars, which in turn causes misallocation and welfare loss.

In this section, we compare the VLS against two alternative market-based policies, which aim at vehicle control. In counterfactual scenario (II), we remove the vehicle lottery and simulate the effect of a “first registration tax” as explained below; and in scenario (III), we replace the vehicle lottery policy with a revised consumption tax scheme. In Hong Kong, the first registration tax system was introduced to encourage the use of environment-friendly petrol private cars with low emissions and high fuel efficiency, which effectively controlled the growth of private cars. Based on the tax system in Hong Kong, we revise the tax rates used in our counterfactual scenario (II) so that it is as effective as the vehicle lottery in controlling vehicle sales. The first registration tax systems in Hong Kong and counterfactual scenario (II) are listed in Table 4. Similarly, China imposed a consumption

\[32\] As shown in Figure 2 to 4, the sales-weighted average prices, horsepower, and fuel efficiency are not in steady state in 2011. So we conduct the counterfactual analysis using the data in 2012 in Beijing.
tax on vehicles to reduce pollution and save energy. Based on the consumption tax rates in 2008, we adjust the tax rates in counterfactual scenario (III) to achieve the same effect as the VLS in controlling vehicle growth in Beijing. Both the current consumption tax rates and the consumption tax rates in counterfactual scenario (III) are shown in Table 5. The vehicle sales in Beijing (2011Q2-2012Q4) are 814,708 under scenario (II) and 816,160 under scenario (III), relative to observed sales of 816,001 under the VLS.

In this section, null scenario stands for the observed facts under the VLS; counterfactual scenario (I) stands for a setting with no policy (benchmark); counterfactual scenario (II) stands for the case where we replace the VLS with the hypothetical first registration tax in Table 4; and counterfactual scenario (III) reflects a setting where we replace the VLS with the hypothetical consumption tax in Table 5.

Table 4: First Registration Tax Rate in Hong Kong and Counterfactual Scenario (II)

<table>
<thead>
<tr>
<th>Class of motor vehicle</th>
<th>Tax rates in Hong Kong</th>
<th>Tax rates in counterfactual scenario (II)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a. on the first HKD 150,000</td>
<td>40%</td>
<td>a. on the first RMB 132,000</td>
</tr>
<tr>
<td>b. on the next HKD 150,000</td>
<td>75%</td>
<td>b. on the next RMB 132,000</td>
</tr>
<tr>
<td>c. on the next HKD 200,000</td>
<td>100%</td>
<td>c. on the next RMB 176,000</td>
</tr>
<tr>
<td>b. on the remainder</td>
<td>115%</td>
<td>d. on the remainder</td>
</tr>
</tbody>
</table>

Note: Tax rates in Hong Kong come from Source: The Transport Department, The Government of the Hong Kong Special Administrative Region. All money is nominal.

Table 5: Consumption Tax Rates in China and Counterfactual Scenario (III)

<table>
<thead>
<tr>
<th>Engine displacement (Liter)</th>
<th>Observed tax rates</th>
<th>Tax rates in counterfactual scenario (III)</th>
</tr>
</thead>
<tbody>
<tr>
<td>≤ 1.0</td>
<td>1%</td>
<td>5.25%</td>
</tr>
<tr>
<td>1.0-1.5</td>
<td>3%</td>
<td>11.50%</td>
</tr>
<tr>
<td>1.5-2.0</td>
<td>5%</td>
<td>17.75%</td>
</tr>
<tr>
<td>2.0-2.5</td>
<td>9%</td>
<td>26.00%</td>
</tr>
<tr>
<td>2.5-3.0</td>
<td>12%</td>
<td>33.25%</td>
</tr>
<tr>
<td>3.0-4.0</td>
<td>25%</td>
<td>50.50%</td>
</tr>
<tr>
<td>&gt; 4.0</td>
<td>40%</td>
<td>69.75%</td>
</tr>
</tbody>
</table>

Note: The observed consumption tax rates come from Ministry of Finance of the People’s Republic of China.

33 In China, three categories of taxes are imposed on a car: the consumption tax, value-added tax (VAT), and vehicle purchase tax; see Xiao and Ju (2014) for more details about these taxes.
5.1 Impact on Fleet Composition

With the estimates under the benchmark specification, we simulate the demand of each product in Beijing in 2012 under different scenarios. To estimate the impact of Beijing's VLS on fleet composition, we first summarize price, horsepower, and fuel efficiency under null scenario and counterfactual scenario (I) of no policy. Then we depict car price distribution, horsepower distribution, and fuel efficiency distribution under the lottery system and counterfactual scenario (I) of no policy. We compare the distributions under these two scenarios to identify the changes in fleet.

Table 6 compares the price, horsepower, and fuel efficiency of the cohort of new passenger vehicles registered in Beijing in 2012 under null scenario and counterfactual scenario (I). As can be seen in Table 6, there are significant differences between counterfactual scenario (I) and null scenario in price, horsepower, and fuel efficiency. Our results indicate that the VLS caused an increase in the sales-weighted average price in Beijing in 2012 by about 42,430 Yuan, an increase of approximately 22.40%. We also find that the sales-weighted average horsepower under lottery system is about 9.01% higher than that under counterfactual scenario (I) of no policy. Moreover, the fleet becomes less fuel efficient. The sales-weighted average fuel efficiency of new vehicles registered under the lottery is 8.09 liters/100km, relative to 7.85 under no policy. These results are consistent with our discussion above: the lottery system will make car buyers in Beijing switch to high-end and more powerful but less fuel efficient vehicles.

Table 6: Price, Horsepower, and Fuel Efficiency Summary Statistics under Null Scenario and Counterfactual Scenario (I) in Beijing in 2012

<table>
<thead>
<tr>
<th>Variables</th>
<th>Counterfactual Scenario (I)</th>
<th>Null Scenario</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>Mean</td>
</tr>
<tr>
<td>Price (1,000 Yuan)</td>
<td>189.42</td>
<td>214.80</td>
<td>231.85</td>
</tr>
<tr>
<td>Horsepower (kw)</td>
<td>105.20</td>
<td>38.17</td>
<td>114.68</td>
</tr>
<tr>
<td>Fuel Efficiency(L/100km)</td>
<td>7.85</td>
<td>1.62</td>
<td>8.09</td>
</tr>
</tbody>
</table>

Note: All money is in 2009 RMB Yuan. The number of observations is 2,964. The mean of price, horsepower, and fuel efficiency are sales-weighted means. The new vehicle sales are 1,066,551 under counterfactual scenario (I) and 531,639 under null 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 under counterfactual scenario (I) and null scenario. We depict the price distribution, horsepower distribution, and fuel efficiency distribution in Figure 5, 6, and 7, respectively. As shown in Figure 5, the cumulative distribution of prices under the lottery system lies on the right of that under counterfactual scenario (I). This implies that households would buy more expensive cars under the lottery system. Similarly, Figure 6 and 7 indicate that the cumulative distribution of horsepower and fuel efficiency shift to the left after removing the lottery system. That is, the lottery system would lead buyers to purchase more powerful but less fuel efficient cars.

Our results imply that households in Beijing switch to high-end, more powerful, but less fuel efficient vehicles due to the policy. Here we provide a possible explanation. Most households in China use their savings to purchase a vehicle (Xiao et al., 2016). Households who do not win the lottery can set aside additional money for vehicle purchase each period. As a result, they have more savings and can afford more expensive cars when they have the right to buy cars. In addition, the households would concentrate their transportation investment on high-end and more expensive vehicles, shifting the fleet toward less fuel efficient vehicles.
It is worthwhile to investigate the underlying mechanism for such change in households’ vehicle choices. We leave this question for future research.
5.2 Impacts on Gasoline Consumption and Pollutant Emissions

Although the vehicle lottery policy is effective to control vehicle population growth in Beijing, the cost of the vehicle restriction is a less fuel-efficient vehicle fleet. Here, we estimate the gas consumption and pollutant emissions under both null scenario and counterfactual scenario (I). The pollutants include carbon dioxide (CO$_2$), particulate matter (PM$_{10}$ and PM$_{2.5}$), nitrogen oxides (NO$_x$), and carbon monoxide (CO)\(^{34}\). Moreover, we also calculate the sales-weighted average fuel efficiency since better fuel economy is associated with lower vehicle emissions (Harrington, 1997).

To quantify gasoline consumption and pollutant emissions, we first need to specify the household’s average annual vehicle miles traveled (VMT) in Beijing and the lifetime of the vehicles. We acquire the average annual VMT data from the 2010 Beijing Household Travel Survey conducted by Beijing Transportation Research Center. The average VMT (100 km) is 161 in Beijing. In addition, we follow the literature and assume that the lifetime of a new vehicle is 15 years (Beresteanu and Li, 2011)\(^{35}\).

The total gasoline consumption in market $t$ is given by

$$\text{GAS}_t^z = \sum_{j \in J_t} q_{tj}^z \times \text{VMT} \times \text{FE}_j \times 15$$

where the superscripts $z = 0, 1, 2, 3$ are respectively used to index null scenario and counterfactual scenario (I), (II), (III), $q_{tj}^z$ is the number of car $j$ at the $z$ scenario, \text{VMT} is the household’s average annual vehicle miles traveled, and \text{FE}_j is the fuel efficiency (liters/100km) of product $j$.

<table>
<thead>
<tr>
<th>Table 7: Average Emissions per Liter Gasoline for Passenger Cars</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>g/liter</td>
</tr>
</tbody>
</table>

Let $e_l$ be the emission volume of pollutant $l$ per gallon of gasoline listed in Table 7\(^{36}\).

\(^{34}\) PM$_{10}$ and PM$_{2.5}$ are particulate matters with diameter less than 10 micrometers and 2.5 micrometers, respectively.

\(^{35}\) While some studies choose 10 years (Li, 2015), different lifetime horizons do not affect the qualitative comparison.

\(^{36}\) When estimating pollutant emissions of vehicles, some studies employ emission per kilometer driven.
obtained $e_l$ from Environmental Protection Agency (EPA) (2008). The total emissions of pollutant $l$ in market $t$ are computed by

$$EM_t^l = \sum_{j \in J_t} q_{tj}^l \times VMT \times FE_j \times e_l \times 15 \quad (16)$$

Table 8 presents the lifetime gas consumption and pollutant emissions under null and counterfactual scenarios. They are calculated for the new passenger cars registered in Beijing in 2012. Previous analysis shows that new vehicle sales would have been 1,066,551 units in the absence of the lottery policy, compared to the observed 531,639 under the lottery system. This implies that new vehicles sales decreased by 50.15% due to the policy. Row 2 shows that the vehicle quota led to a lower fleet fuel efficiency. Row 3 suggests that Beijing’s vehicle lottery policy reduced fuel consumption by $0.98 \times 10^{10}$ liters, a decline of approximately 48.69%. Similarly, the emissions of each pollutant were reduced by 48.69% with vehicle restriction.

An interesting finding is that the percentage reductions in gasoline consumption and pollutant emissions are not as much as that in new vehicle sales. This is because of the controversial effects of the policy. As shown in above analysis, the policy effectively decreased new vehicle sales in Beijing, which in turn reduced fuel consumption. However, it also shifted the fleet toward less fuel efficient vehicles.

Here, we use fuel consumption as illustration. Let $Q_t^0$ and $Q_t^1$ be the total sales product $j$ in market $t$ at the null and counterfactual scenario (I), respectively. $r_{tj}^0$ and $r_{tj}^1$ are the relative market shares of product $j$ in market $t$ under null and counterfactual scenario (I). In market $t$, the change in gas consumption is given by

$$\Delta GAS_t = \sum_{j \in J_t} q_{tj}^0 \cdot VMT \cdot FE_j \cdot 15 - \sum_{j \in J_t} q_{tj}^1 \cdot VMT \cdot FE_j \cdot 15$$

$$= 15 \cdot VMT \cdot \left[ \sum_{j \in J_t} Q_t^0 \cdot r_{tj}^0 \cdot FE_j - \sum_{j \in J_t} Q_t^1 \cdot r_{tj}^1 \cdot FE_j \right]$$

$$= \left[ -15 \cdot VMT \cdot (Q_t^1 - Q_t^0) \sum_{j \in J_t} r_{tj}^1 \cdot FE_j \right] + \left[ 15 \cdot VMT \cdot Q_t^0 \sum_{j \in J_t} (r_{tj}^0 - r_{tj}^1) \cdot FE_j \right]$$

[Xiao and Zhou, 2013; Li and Jones, 2015]. Instead, we use emission factors on a per gallon of gasoline basis since more gasoline combusted contributes to higher emissions of pollutants [Harrington, 1997].
Table 8: Counterfactual Analysis under Different Scenarios in Beijing 2011Q2-2012Q4

<table>
<thead>
<tr>
<th>Counterfactual scenario (I) (Baseline)</th>
<th>Null scenario</th>
<th>Counterfactual scenario (II)</th>
<th>Counterfactual scenario (III)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales of new passenger cars</td>
<td>1,066,551</td>
<td>531,639</td>
<td>493,148</td>
</tr>
<tr>
<td>Fleet fuel efficiency (Liters/100km)</td>
<td>7.85</td>
<td>8.09</td>
<td>7.36</td>
</tr>
<tr>
<td>Gasoline consumption (liters)</td>
<td>$2.02 \times 10^{10}$</td>
<td>$1.04 \times 10^{10}$</td>
<td>$0.88 \times 10^{10}$</td>
</tr>
<tr>
<td>CO$_2$ emissions in tons</td>
<td>$4.75 \times 10^7$</td>
<td>$2.43 \times 10^7$</td>
<td>$2.06 \times 10^7$</td>
</tr>
<tr>
<td>PM$_{10}$ emissions in tons</td>
<td>566.41</td>
<td>290.62</td>
<td>245.45</td>
</tr>
<tr>
<td>PM$_{2.5}$ emissions in tons</td>
<td>525.95</td>
<td>269.89</td>
<td>227.92</td>
</tr>
<tr>
<td>NO$_x$ emissions in tons</td>
<td>$8.93 \times 10^4$</td>
<td>$4.58 \times 10^4$</td>
<td>$3.87 \times 10^4$</td>
</tr>
<tr>
<td>CO emissions in tons</td>
<td>$12.11 \times 10^5$</td>
<td>$6.21 \times 10^5$</td>
<td>$5.25 \times 10^5$</td>
</tr>
<tr>
<td>Change in external costs (billion Yuan)</td>
<td>-</td>
<td>$-54.70$</td>
<td>$-63.63$</td>
</tr>
<tr>
<td>Change in consumer welfare (billion Yuan)</td>
<td>-</td>
<td>$-151.66$</td>
<td>$-101.52$</td>
</tr>
<tr>
<td>Change in government revenue (billion Yuan)</td>
<td>-</td>
<td>0</td>
<td>10.24</td>
</tr>
<tr>
<td>Change in social welfare (billion Yuan)</td>
<td>-</td>
<td>$-96.96$</td>
<td>$-27.65$</td>
</tr>
</tbody>
</table>

Note: All money is in 2009 Yuan. The external costs are calculated based on a discount rate of 5% during 15 years.
where the first term represents the effect on gasoline consumption due to sales decrease alone, whereas the second term measures the impact on gasoline consumption because of fleet fuel efficiency changes. In our analysis, the license plate restriction would have reduced the gas consumption by 50.09% in Beijing holding fleet fuel efficiency constant, changes in fleet fuel efficiency increased fuel consumption by only 1.40%.

5.3 Welfare Analysis

In this subsection, we estimate the welfare effect of the policy in 2012. In our study, we define the social welfare as consumer welfare plus government revenue minus external costs related to vehicle usage.

In this paper, we use compensating variation (CV) as a measure of the change in consumer welfare due to a policy. Since the marginal utility of income is nonlinear in our specification, we cannot calculate CV with the approach used by Nevo (2000), Nevo (2003), and Xiao and Ju (2014)\(^{37}\). Given our utility function (1), we follow Small and Rosen (1981) and Herriges and Kling (1999) and derive our estimation of the expected compensating variation. As in previous studies, let \(w_0\) and \(w\) denote the case without policy versus the case with a policy. The expected CV of household \(i\) in market \(t\) due to a policy is given by\(^{38}\)

\[
E(CV_i \mid y_i, v_i) = E_{\varepsilon} \left\{ y_i - \exp \left[ \ln y_i + \frac{U_{iit}^{wo} - U_{iit}^w}{\eta \ln p_{mt}^w} \right] \right\}
\]

(17)

where \(U_{iit}^w = \max_{j=1, \ldots, J_t} u_{ijt}^w\) and \(U_{iit}^{wo} = \max_{j=1, \ldots, J_t} u_{ijt}^{wo}\). \(y_i\) is household income, and \(v_i\) is a vector of unobservable household characteristics. Then the measure of total consumer welfare in market \(t\) can be calculated as

\[
CV_t = Q_t^{wo} \int E(CV_i \mid y_i, v_i) dP(y) dP(v) = \frac{Q_t^{wo}}{n_s} \sum_{i=1}^{n_s} E(CV_i \mid y_i, v_i)
\]

(18)

\(^{37}\)In those studies, consumer \(i\)'s indirect utility function from product \(j\) in market \(t\) is \(u_{ijt} = V_{ijt} + \epsilon_{ijt}\), where \(\epsilon_{ijt}\) follows i.i.d. extreme value distribution. For a logit discrete choice model, if the marginal utility of income is constant, then the expected compensating variation of household \(i\) due to a policy is given by

\[
E(CV_{i}) = \frac{\ln \sum_{j=1}^{J_t} \exp(V_{ijt}^{wo}) - \ln \sum_{j=1}^{J_t} \exp(V_{ijt}^w)}{MU}\]

where \(w\) and \(wo\) denote with and without the policy, respectively. Here \(MU\) is the constant marginal utility of income.

\(^{38}\)In Appendix B, we give details of the derivation.
where $Q_{w}^{t}$ is the number of vehicles sold in market $t$ under no policy. In this paper, we follow the simulated method developed by Herriges and Kling (1999) for consumer welfare computation. We first generate $n_s = 150$ households from the distributions of $y$ and $v$ by Halton sequences for each quarter in Beijing. For each household, we simulate 200 draws from the distribution of $e_{ijt}$ for each product. With simulated $e_{ijt}$, we can compute each household’s expected CV in equation (17). Finally, the consumer welfare in market $t$ can be calculated by equation (18).  

We now turn to external costs associated with vehicle usage. Parry et al. (2007) argue that vehicle usage could cause various externalities, such as air pollution and traffic congestion. Creutzig and He (2009) estimate the external costs of one gallon of gasoline consumption to be 9.7 Yuan in Beijing, i.e., $6.02 per gallon of gasoline.  

Given the fact that the gasoline tax in China includes 1 Yuan per liter to deal with externalities, we follow Li (2015) and use 8.7 Yuan (in 2012 term) per gallon of gasoline as the external costs in our analysis. The total external costs are calculated based on an annual discount rate of 5% during the vehicles’ lifetime.

Table 8 presents our empirical results on welfare. On the benefits side, the vehicle lottery significantly reduces gas consumption and pollutant emissions in Beijing. The externality reduction from the lottery system is estimated to be 54.70 billion Yuan during a 15-year time span. On the cost side, the vehicle quota system leads to about 151.66 billion Yuan loss in consumer welfare. Consumer welfare loss from the lottery policy is due to: (1) those households who have demand for private vehicles but cannot purchase cars since they do not win the lottery; and (2) the lottery allocates vehicles to households who do not necessarily have the highest willingness-to-pay. Overall, the reduction in external costs is dominated by the consumer welfare loss and the vehicle lottery causes a social welfare loss of 96.96 billion Yuan.

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39 We also tried 300 draws of $e_{ijt}$ but that made little difference in our estimations.

40 Similarly, Parry and Timilsina (2009) find that the external costs from vehicle usage is $6.06 per gallon of gasoline consumed in Mexico city, which is a comparable city to Beijing.
5.4 Alternative Policies and Comparisons

Generally, market-based mechanisms (e.g., taxes) achieve better allocative efficiency than non-market based mechanisms (e.g., lottery). Therefore, we check the effectiveness of the two alternative market-based policies discussed at the beginning of Section 5 and in Table 4 and 5, i.e., a first registration tax system and a consumption tax scheme. The results are shown in Table 8.

In counterfactual scenario (II), we apply a first registration tax system to Beijing. As shown in Table 8, the fleet efficiency under the registration tax scheme is better compared with vehicle lottery. Moreover, the gas consumption and pollutant emissions are lower in counterfactual scenario (II). The consumer welfare loss is much smaller under this tax system because tax policies achieve better efficiency by allocating the resource to those with the highest willingness to pay. Specifically, the social welfare would increase by 69.31 billion Yuan in Beijing in 2012 if Beijing municipal government replaced the vehicle lottery with the first registration tax system. Also, such a tax policy could generate 10.24 billion Yuan tax revenue for Beijing government, which makes it likely to gain political support.

Column 5 in Table 8 presents the market outcomes under scenario (III) with a hypothetical consumption tax scheme. We find that the fleet is more fuel efficient under the consumption tax system. This result implies that such consumption tax can further lower gas consumption by 1.3 billion liters. We also find that the consumption tax policy generates less pollutant emissions relative to the vehicle quota system. In terms of social welfare, such a tax policy only leads to 17.13 billion Yuan loss in social welfare in Beijing in 2012, relative to welfare loss of 96.96 billion Yuan under the VLS. That is to say, Beijing loses 79.83 billion Yuan in welfare in 2012 by using the lottery system rather than a consumption tax to control vehicle registrations.

In a related paper, Li (2015) compares Beijing’s lottery system with a uniform-price auction to study the welfare consequences of these mechanisms. He finds that the social welfare (consumer welfare plus government revenue minus external costs) loss from the lottery sys-

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41 The tax rates were shown in Table 5. The tax rates are designed so that the fleet size is the same under both vehicle lottery policy and the consumption tax regime.
tem is about 58 billion Yuan in Beijing in 2012, compared with a uniform price auction. Our study indicates that the lottery system leads to welfare loss of nearly 69.31 and 79.83 billion Yuan compared with the first registration tax scheme and the consumption tax system, respectively. Thus, a uniform price auction is superior in terms of improving social welfare. However, Li (2015) also finds that fleet efficiency of new vehicles sold under the auction system is lower than that under the VLS. In contrast, our paper reveals that our tax systems shift new vehicle purchases toward more fuel efficient cars and generate a more fuel efficient fleet relative to the VLS. Thus, these results suggest that the tax schemes work better than the auction system for environmental purposes.

From the above analysis, we find that the vehicle lottery system is not the first choice to control vehicle growth and air pollution. Beijing municipal government could consider some market-based policies, such as tax policies, which can be more effective in slowing down vehicle increase and reducing pollutant emissions.

6 Conclusion

With the rapid growth in vehicle population, problems such congestion, energy shortages, air pollution and its health consequences have become a major concern in Beijing and many other cities worldwide. To control vehicle growth and thereby address related environmental issues, Beijing 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, fuel consumption, pollutant emissions, and social welfare. 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 and compare with other policies, we then conduct counterfactual analysis based on the model estimates.

Our main results suggest that Beijing’s vehicle lottery is effective in limiting new vehicle sales and reducing gasoline consumption and air pollution. However, vehicle fleet composition changes due to the policy. The vehicle quota system shifts the demand for new vehicles
toward less fuel efficient cars because of households’ behavioral responses, such as concentrating their transportation investment into single high-end but less fuel efficient vehicles. This change can undermine the potential benefits. In addition, our analysis shows that this system leads to a welfare loss since it arbitrarily reduces demand for vehicles regardless of the willingness to pay for new vehicles.

The vehicle lottery system 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. While this vehicle quota system may seem a reasonable approach for resolving vehicular environmental issues, our counterfactual analysis shows that a progressive tax system works better than the vehicle lottery policy in reducing fuel consumption and air pollution. Moreover, we find that, relative to the lottery system, such a tax scheme can achieve the same effect in controlling vehicle growth but improving fleet fuel efficiency and producing a smaller welfare loss. This implies that other cities could consider other options to the lottery system in an effort to control vehicle, gas consumption, and air pollution.

There are several worthwhile directions for future research. First, our conclusion is based on the assumption that the lottery does not change driving patterns. Examining how the lottery system affects driving patterns would be helpful to accurately assess the effects of the policy. Second, our results suggest that Beijing’s vehicle lottery system shifts households’ purchases toward high-end vehicles, which in turn could affect the local automotive market structure. Exploring the impact of this system on the market structure has important implications for the industry. Finally, future research could consider a dynamic model to investigate how households choose among available products or wait to purchase in the future, which helps to understand the policy effects on consumers’ behavior.
References


Appendix A

Table 1: Policy Impact on New Passenger Cars Registration in Beijing

<table>
<thead>
<tr>
<th>Year</th>
<th>City</th>
<th>No. of Households (10,000)</th>
<th>Average Household Income (in RMB Yuan)</th>
<th>GDP per Capita (Yuan/person)</th>
<th>Average Consumption Expenditure per Capita (Yuan/person)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>Beijing</td>
<td>636.29</td>
<td>74,866.40</td>
<td>66,940</td>
<td>17,885</td>
</tr>
<tr>
<td>2010</td>
<td>Beijing</td>
<td>668.10</td>
<td>81,404.40</td>
<td>73,856</td>
<td>19,929</td>
</tr>
<tr>
<td>2011</td>
<td>Beijing</td>
<td>687.86</td>
<td>88,838.10</td>
<td>81,658</td>
<td>21,973</td>
</tr>
<tr>
<td>2012</td>
<td>Beijing</td>
<td>704.89</td>
<td>98,466.30</td>
<td>87,475</td>
<td>23,980</td>
</tr>
<tr>
<td>2009</td>
<td>Nanjing</td>
<td>230.84</td>
<td>68,351.04</td>
<td>55,290</td>
<td>16,339</td>
</tr>
<tr>
<td>2010</td>
<td>Nanjing</td>
<td>237.00</td>
<td>75,876.16</td>
<td>63,771</td>
<td>18,156</td>
</tr>
<tr>
<td>2011</td>
<td>Nanjing</td>
<td>240.08</td>
<td>86,940.00</td>
<td>76,263</td>
<td>20,763</td>
</tr>
<tr>
<td>2012</td>
<td>Nanjing</td>
<td>241.62</td>
<td>96,979.74</td>
<td>88,525</td>
<td>23,493</td>
</tr>
<tr>
<td>2009</td>
<td>Shenzhen</td>
<td>307.10</td>
<td>94,752.24</td>
<td>84,147</td>
<td>21,526</td>
</tr>
<tr>
<td>2010</td>
<td>Shenzhen</td>
<td>322.11</td>
<td>104,266.37</td>
<td>94,296</td>
<td>22,807</td>
</tr>
<tr>
<td>2011</td>
<td>Shenzhen</td>
<td>332.30</td>
<td>114,990.88</td>
<td>110,421</td>
<td>24,080</td>
</tr>
<tr>
<td>2012</td>
<td>Shenzhen</td>
<td>328.58</td>
<td>130,781.43</td>
<td>123,247</td>
<td>26,728</td>
</tr>
<tr>
<td>2009</td>
<td>Tianjin</td>
<td>356.92</td>
<td>61,637.79</td>
<td>62,574</td>
<td>14,801</td>
</tr>
<tr>
<td>2010</td>
<td>Tianjin</td>
<td>366.20</td>
<td>69,476.84</td>
<td>72,994</td>
<td>16,562</td>
</tr>
<tr>
<td>2011</td>
<td>Tianjin</td>
<td>383.35</td>
<td>76,455.24</td>
<td>85,213</td>
<td>18,424</td>
</tr>
<tr>
<td>2012</td>
<td>Tianjin</td>
<td>399.92</td>
<td>84,435.27</td>
<td>93,173</td>
<td>20,024</td>
</tr>
</tbody>
</table>

Note: The data are from various issues of yearbook by cities and years. All money is nominal.
Appendix B

In this appendix, we will derive the compensating variation of household $i$. In our paper, the utility function is defined by

$$u_{ijt}(y_i, v_i, p_{jt}, x_{jt}, \delta_{jt}, \varepsilon_{ijt}) = \delta_{jt} + \sum_{k=1}^{K} \sigma_k x_{jkt} v_{it}^k + (\eta \ln y_i + \sigma_p v_p^p_i) \ln p_{jt} + \varepsilon_{ijt} \quad (19)$$

Let $w_0$ and $w$ denote the cases without and with policy, respectively. In case without policy, the household chooses product $l$, i.e.,

$$U_{il}^{w_0}(y_i, v_i, p_{l_0}, x_{l_0}, \delta_{l_0}, \varepsilon_{il}) = \max_{j=1, \ldots, J_t} u_{ijt}(y_i, v_i, p_{jt}, x_{jt}, \delta_{jt}, \varepsilon_{ijt})$$

In case with policy, the household chooses product $m$, so

$$U_{im}^w(y_i, v_i, p_{m_0}, x_{m_0}, \delta_{m_0}, \varepsilon_{im}) = \max_{j=1, \ldots, J_t} u_{ijt}(y_i, v_i, p_{jt}, x_{jt}, \delta_{jt}, \varepsilon_{ijt})$$

The compensating variation (CV) is implicitly defined by

$$U_{il}^{w_0}(y_i, v_i, p_{l_0}, x_{l_0}, \delta_{l_0}, \varepsilon_{il}) = U_{im}^w(y_i - CV_{it}, v_i, p_{m_0}, x_{m_0}, \delta_{m_0}, \varepsilon_{im})$$

Using equation (19), we rearrange the above equation and obtain

$$U_{il}^{w_0} = U_{im}^w - \eta \ln y_i \ln p_{m_0}^w + \eta \ln (y_i - CV_{it}) \ln p_{m_0}^w$$

Rearranging the equation gives the compensating variation

$$CV_{it} = y_i - \exp \left[ \ln y_i + \frac{U_{il}^{w_0} - U_{im}^w}{\eta \ln p_{m_0}^w} \right]$$