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

Ziying Yang\textsuperscript{a}  Félix Muñoz-García\textsuperscript{b}  Manping Tang\textsuperscript{c,†}

\textsuperscript{a} School of Finance, Southwestern University of Finance and Economics, Chengdu, Sichuan, China
\textsuperscript{b} School of Economic Sciences, Washington State University, Pullman, WA, United States
\textsuperscript{c} College of Management, Sichuan Agricultural University, Chengdu, Sichuan, China

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 potential buyers. This paper investigates the effect of this policy on fleet composition, fuel consumption, and air pollution. 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 reduced new passenger vehicle sales by 49.15%, fuel consumption by 46.65%, and pollutant emissions by 46.65% in 2011 and 2012. Also, such policy shifted new auto purchases towards high-end but less fuel efficient vehicles, offsetting part of its positive effect on the environment.

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

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

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†Corresponding author.

Email: ziyying1988@gmail.com (Z. Yang), fmunoz@wsu.edu (F. Muñoz-García), tangmp.sicau@gmail.com (M. Tang).
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%. 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.

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) relying on forecasts about Beijing’s future population or GDP. Their estimations of fuel consumption are, however, based on average fleet fuel efficiency; as opposed to our study which considers the specific fuel efficiency of each car model thus providing more accurate estimates about the policy effects. 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 is being adopted by other large cities in the region. It also provides insights for cities abroad that are facing similar congestion and pollution problems.

Our paper mainly focuses on the effect of Beijing’s VLS on fleet composition. We also investigate its impact on gas consumption and pollutant emissions. First, 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

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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 Guiyang adopted license lotteries in July 2011. Guangzhou, Tianjin, Hangzhou, and Shenzhen implemented a hybrid system combining lottery and auction in July 2012, January 2014, May 2014, and December 2014, respectively. Other large Chinese cities (Chengdu, Chongqing, Qingdao, and Wuhan) are considering enacting similar control policies.
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 outcomes under the counterfactual scenario of no policy and compare them with the observed facts.

Our study provides interesting findings. First, Beijing’s VLS reduced new passenger car sales by 49.15%, gas consumption by 46.65%, and pollutant emissions by 46.65% in 2011 and 2012. Second, our results indicate 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. Our analysis indicates that fuel consumption increased by 4.96% in Beijing in 2011 and 2012 due to fleet fuel composition changes caused by VLS.

**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 analyze the effect of the VLS since more cities are adopting this policy. 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 Beijing's hypothetical population and GDP on that future date. However, this literature cannot disentangle the effect of VLS from other confounding factors, such as changes in household income or auto market structure. Incorporating these
features can yield better predictions about the effects of existing policies (Chetty, 2015). Our work derives vehicle demand from household preferences and their choices. Hence, our estimates should then contribute to this literature, helping to provide more accurate estimates. 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. 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 insti-
tutions. 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 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[^2]. Moreover, these vehicles are banned to travel within the 5th ring road (inclusively) during peak hours.

### 2.2 Data

#### 2.2.1 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


[^2]: The 5th ring road is about 98.58 km in length and the area within it is about 700 km².
Nanjing, Shenzhen, and Tianjin to facilitate identification. These cities did not have policies on vehicle ownership or vehicle usage during our sample period. The characteristics of these four cities are shown in Appendix A (Table 1). Generally, these cities are similar in average household income, GDP per capita, and average consumption expenditure per capita. In addition, Li (2017) proves common trend of vehicle sales in Tianjin and Beijing. We also include Nanjing and Shenzhen because a combination of units often provides a better comparison than any single unit alone (Abadie et al., 2010).

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, quantity, and purpose of use (private or business). 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. A product is defined as a unique combination of the model year, manufacturer, brand, model, engine displacement, and bodystyle. 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. 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. There are 38,359 observations in our sample.

Figure 1 plots quarterly sales of new vehicles in Beijing, Nanjing, Shenzhen, and Tianjin. Figure 1 reflects that these cities followed a similar trend before 2011. In addition, there were strong seasonal effects, whereby sales increase at the end of each year, likely due to the sales quota required from the manufacturer to retailers. Finally, new vehicle sales in Beijing increase dramatically in the fourth quarter of 2010 and then decrease sharply in the

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6 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.
7 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.
[Abadie and Gardeazabal, 2003] and [Abadie et al., 2010] develop synthetic control method to reduce the ambiguity about the choice of the control unit comparison. With city characteristics (such as GDP per capita) and fleet characteristics (such as fleet fuel efficiency) in these cities during the pre-policy period, we apply the method to Nanjing, Shenzhen, and Tianjin. We find that they are valid comparison cities for Beijing.
9 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.
first quarter of 2011. Since Beijing’s 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 announcement effects, we drop the last quarter in 2010 in Beijing in our estimation.

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, taxes, and government subsidies. 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 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).\(^{10}\) 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.\(^{11}\)

Table 1 provides the summary statistics of our sample. Both quarterly sales and prices have large variations. The most popular passenger car has a quarterly sale of 6,620 units whereas the least popular car had only one sale. The average price is 199,600 Yuan, rang-

\(^{10}\) Fuel efficiency data are obtained from Ministry of Industry and Information Technology of China.

\(^{11}\) Consumer Price index are from National Bureau of Statistics of the People’s Republic of China.
ing from 29,090 to 2,197,410 Yuan. The average price is higher than the average household income. Horsepower and engine size are correlated with vehicle performance. The most powerful vehicle has a horsepower of 250 kw, while the least has a horsepower of 26.5 kw. Engine size varies from 0.8L to 5.7L. Vehicle weight and vehicle size are indicators of comfort and safety. The lightest car weighs 650 kg, whereas the heaviest one weighs 2,890 kg. The largest vehicle is 11.57 m$^2$, while the smallest one is 4.20 m$^2$. Fuel efficiency and gas expenditure are used to measure vehicle fuel consumption performance. The least fuel efficient vehicle drive 5.24 km per liter of gasoline, while the most fuel efficient can drive 37.04 km.

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>117.42</td>
<td>300.82</td>
<td>1</td>
<td>6,620</td>
</tr>
<tr>
<td>Price (1,000 Yuan)</td>
<td>199.60</td>
<td>192.97</td>
<td>29.09</td>
<td>2197.41</td>
</tr>
<tr>
<td>Weight (1,000 kg)</td>
<td>1.37</td>
<td>0.29</td>
<td>0.65</td>
<td>2.89</td>
</tr>
<tr>
<td>Horsepower (kw)</td>
<td>100.74</td>
<td>34.10</td>
<td>26.50</td>
<td>250.00</td>
</tr>
<tr>
<td>Vehicle size (m$^2$)</td>
<td>8.02</td>
<td>34.10</td>
<td>26.50</td>
<td>250.00</td>
</tr>
<tr>
<td>Fuel efficiency (km/liter)</td>
<td>13.02</td>
<td>2.17</td>
<td>5.24</td>
<td>37.04</td>
</tr>
<tr>
<td>Gas expenditure (Yuan/km)</td>
<td>0.53</td>
<td>0.10</td>
<td>0.16</td>
<td>1.42</td>
</tr>
<tr>
<td>Engine size (L)</td>
<td>1.84</td>
<td>0.50</td>
<td>0.80</td>
<td>5.70</td>
</tr>
</tbody>
</table>

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.

The second data set is the household income distribution in each city and year, which is constructed through the 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 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. Follow-

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12 Chinese Household Income Survey is a national representative survey conducted by University of Michigan and China Institute for Income Distribution. More details can be found on website [http://www.ciidbnu.org/index.asp](http://www.ciidbnu.org/index.asp)
ing the literature, we assume that the logarithm of household income follows the normal distribution.

2.2.2 Stylized Facts

The above summary statistics do not show the changes of vehicle characteristics across the cities over time. Figure 2-4 display 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. 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 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 induce buyers to switch to high-end, more powerful, but less fuel efficient cars.

![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

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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.
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'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). This methodology is widely used to examine the impacts of vehicle policies. For
example, Diamond (2009) uses this method to study the impact of government incentives for hybrid-electric vehicles in U.S..

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 $i$ denote a household. The utility from the outside option is normalized to $\varepsilon_{0mt}$, 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

$$u_{ijmt} = x_{jmt} \beta_i + \alpha_i \ln p_{jmt} + \lambda_{bs} \text{bodystyle}_j + \lambda_{fd} \text{firm}_j + \lambda_{q} \text{quarter}$$

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.$^{14}$ $\xi_{jmt}$ is the unobserved (to researchers) characteristics of product $j$ in market $m$ at time $t$, such as product quality. $\varepsilon_{ijmt}$ 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 $\alpha_i$ and $\beta_i$. In particular, $\alpha_i$ is household $i$’s marginal utility from income and it is given by

$$\alpha_i = \bar{\alpha} + \eta \ln y_{imt} + \sigma_p v^p_i$$

where $y_{imt}$ is household income, and $v^p_i$ is unobserved household characteristics that affect household preferences and follow a standard normal distribution. Since households with a

$^{14}$Vehicle bodystyle includes sedan, SUV, MPV, station wagon, and coupe.
higher income \( y_{imt} \) 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 as

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

where \( \hat{\beta}_k \) 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

\[
u_{ij} = \delta_{jmt} + \mu_{ijmt} + \epsilon_{ijmt}
\]

where the utility function is decomposed into a mean utility

\[
\delta_{jmt} = \sum_{k=1}^{K} x_{jkmt} \hat{\beta}_k + \bar{\alpha} \ln p_{jmt} + \lambda \text{dummies} + \xi_{jmt}
\]

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

\[
\mu_{ijmt} = \sum_{k=1}^{K} \sigma_k x_{jkmt} v_i^k + (\eta \ln y_{imt} + \sigma_p v_p^i) \ln p_{jmt}
\]

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

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

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

where \( p_{mt} = (p_{1mt}, ..., p_{Jmt})' \) and \( X_{mt}^d \) includes \( x_{jmt} \), and dummy variables. \( \theta \) 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. \( 1(\text{saving}_{imt} \geq p_{jmt}) \) 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., \( \text{saving}_{imt} = y_{imt} \cdot 5 \).

If \( N_{mt} \) is the market size in market \( m \) at time \( t \), the demand for product \( j \) is \( N_{mt} \cdot s_{jmt} \).

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.

### 3.2 Identification and Estimation

After the idiosyncratic error term \( \varepsilon_{ijmt} \) is integrated out analytically, the econometric error term will be the unobserved product characteristics, \( \xi_{jmt} \), 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 \( \xi_{jmt} \), 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 \( ns \) draws from the distributions of \( v \) and \( y \). The simulated market shares are calculated as

\[
s_{pred}^{jmt} (p_{mt}, x_{mt}', \xi_{mt}, \theta) = \frac{1}{nS} \sum_{i=1}^{nS} e^{\delta_{jmt} + \mu_{ijmt}} \cdot 1(\text{saving}_{imt} \geq p_{jmt}) \left( 1 + \sum_{r=1}^{J} e^{\delta_{rmt} + \mu_{irmt}} \cdot 1(\text{saving}_{imt} \geq p_{rmt}) \right) \tag{9}
\]

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

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15 See Xiao et al. (2017) for more details about reasons for saving setting.

16 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.

17 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.
market shares from the data for a given $\theta_2$: 

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

However, analytical solutions for $\delta_{mt}$ 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:

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

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

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

The parameters $\theta_1$ in equation (12) can be estimated by two-stage least squares (2SLS) using instrumental variables (IVs). The demand unobservable $\xi_{jmt}$ is a function of prices, $X_{jmt}^{d}$, the observed market shares, and parameters. The GMM estimator $\hat{\theta}$ solves the problem:

$$\min_{\theta} Q(\theta) = \min_{\theta} (\xi(\theta)'Z)W(Z'\xi(\theta))$$  \hfill (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 displacement), the sum of

\[18\] See Berry et al. (1995) for a proof of convergence.

\[19\] 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.
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.

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 \(\ln(income)\).

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).

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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.

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.
Table 2: Estimation Results for the Model

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coef.</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Parameters in the mean utility ($\theta_1$)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.1054**</td>
<td>2.1023</td>
</tr>
<tr>
<td>Ln(price)</td>
<td>-9.0232***</td>
<td>2.4291</td>
</tr>
<tr>
<td>Ln(horsepower)</td>
<td>2.7730**</td>
<td>1.1501</td>
</tr>
<tr>
<td>Weight</td>
<td>2.5713***</td>
<td>0.9104</td>
</tr>
<tr>
<td>Gas expenditure (Yuan/km)</td>
<td>-0.6402***</td>
<td>0.2221</td>
</tr>
<tr>
<td>Vehicle size</td>
<td>0.7581***</td>
<td>0.0739</td>
</tr>
<tr>
<td>Engine size</td>
<td>0.2135</td>
<td>0.2237</td>
</tr>
<tr>
<td><strong>Random coefficients ($\sigma$)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.3293</td>
<td>1.2574</td>
</tr>
<tr>
<td>Ln(price)</td>
<td>-0.5962***</td>
<td>0.1168</td>
</tr>
<tr>
<td>Ln(horsepower)</td>
<td>0.3249***</td>
<td>0.1097</td>
</tr>
<tr>
<td>Weight</td>
<td>-0.2223</td>
<td>0.5193</td>
</tr>
<tr>
<td>Gas expenditure (Yuan/km)</td>
<td>0.0092</td>
<td>1.0609</td>
</tr>
<tr>
<td>Vehicle size</td>
<td>0.0003</td>
<td>0.0749</td>
</tr>
<tr>
<td>Engine size</td>
<td>0.0339</td>
<td>0.2371</td>
</tr>
<tr>
<td><strong>Interactions with Ln(income) ($\eta$)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln(price)</td>
<td>0.5629**</td>
<td>0.2690</td>
</tr>
</tbody>
</table>

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%. 
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 \( \ln \text{price} \) and \( \ln \text{income} \) 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 Counterfactual Analysis

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.

#### 4.2.1 Impact on New Vehicle Sales in Beijing

Table 3 presents the new vehicle sales in Beijing with and without VLS. It is shown that sales under no VLS would have been 205,916 in 2010Q4, whereas the observed number was 256,175. This increase could be mainly caused by panic buying. With the announcement of license plate restrictions in Beijing, consumers brought their vehicle purchases forward. Moreover, the new vehicle sales under the counterfactual scenario are 750,499 and 949,950 in 2011 and 2012, respectively. Compared with observed sales in 2011 and 2012 under the policy, the lottery reduced new vehicle registrations in Beijing by 55.04% in 2011 and 44.50% in 2012.\(^{22}\) This suggests that the policy successfully controlled vehicle growth in Beijing.

\(^{22}\) The observed sales in 2011 and 2012 are 337,451 and 527,183, respectively. Sales exceed the yearly quota, i.e., 211,200, because those who destroy, sell, or trade in their existing cars, can retain their license plates to register new vehicles.
### 4.2.2 Impact on Fleet Composition

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

Table 4 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 4, 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 helped car buyers in Beijing switch to high-end and more powerful but less fuel efficient vehicles.

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 5, 6, and 7 respectively. As shown in Figure 5, 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.
Table 4: Price, Horsepower, and Fuel Efficiency Summary Statistics in Beijing in 2012

<table>
<thead>
<tr>
<th>Variables</th>
<th>Without VLS</th>
<th>With VLS</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>181.11</td>
<td>171.74</td>
<td>243.55</td>
</tr>
<tr>
<td>Horsepower (kw)</td>
<td>100.98</td>
<td>31.30</td>
<td>113.35</td>
</tr>
<tr>
<td>Fuel Efficiency(km/L)</td>
<td>13.41</td>
<td>2.09</td>
<td>12.85</td>
</tr>
</tbody>
</table>

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%.

Similarly, Figure 6 and 7 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 would lead buyers to purchase more powerful but less fuel efficient cars.

A possible explanation for this result could be that VLS changed the pool of consumers in auto market, e.g., larger proportion of wealthy households. The VLS, however, randomly assigns licenses to potential buyers, implying that winners are a representative sample of the population of buyers (if the structure of potential buyers did not change). As a result, fleet composition should remain the same. However, our analysis finds that winners tend to buy high-end, less fuel-efficient vehicles, indicating that the policy may cause a change in
distribution of potential buyers. It is worthwhile to investigate why households change their consumption toward high-end but less fuel efficient cars after the VLS, because this would provide the policy marker a guideline of what to expect if a similar policy is implemented in other cities. We leave this question for future research.
4.2.3 Impacts on Gasoline Consumption and Pollutant Emissions

In this section, we estimate the effects of VLS on gas consumption and pollutant emissions in 2011 and 2012. Pollutants include carbon dioxide (CO$_2$), particulate matter (PM$_{10}$), nitrogen oxides (NO$_x$), and carbon monoxide (CO)$^{23}$

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 is 16,100 km per year in Beijing.$^{24}$ In addition, we follow the literature and assume that the lifetime of a new vehicle is 15 years.$^{25}$

The total gasoline consumption in market $m$ at time $t$ is given by

$$GAS^z_{mt} = \sum_{j \in J_{mt}} q^z_{jmt} \times VMT \times FC_j \times 15 \quad (14)$$

where the superscripts $z = 0, 1$ are respectively used to index with and without VLS, $q^z_{jmt}$ is the number of car $j$ at the $z$ scenario, $VMT$ is the household’s average annual vehicle miles traveled, and $FC_j$ is the fuel consumption per km (liters/km) of product $j$.

<table>
<thead>
<tr>
<th></th>
<th>CO$_2$</th>
<th>PM$_{10}$</th>
<th>NO$_x$</th>
<th>CO</th>
</tr>
</thead>
<tbody>
<tr>
<td>g/liter</td>
<td>2345.649</td>
<td>0.028</td>
<td>4.412</td>
<td>59.851</td>
</tr>
</tbody>
</table>

Let $e_l$ be the emission volume of pollutant $l$ per gallon of gasoline listed in Table 5, obtained from the Environmental Protection Agency (EPA) (2008). Total emissions of pollutant $l$ in market $m$ at time $t$ are computed by

$$EM^z_{mt} = \sum_{j \in J_{mt}} q^z_{jmt} \times VMT \times FC_j \times e_l \times 15 \quad (15)$$

$^{23}$ PM$_{10}$ is particulate matters with diameter less than 10 micrometers.

$^{24}$ Following a similar approach as Li (2017) and Xiao et al. (2017), we assume that VLS does not affect VMT. Since license plates are allocated by random draw in the lottery, VLS does change vehicle usage cost. As shown in previous sections, however, VLS decreased the number of vehicles on road and congestion, which could lead individuals to drive more, thus increasing VMT. In this case, our results may overestimate the reductions in gas consumption and pollutant emissions.

$^{25}$ Different lifetime horizons do not affect the qualitative comparison.
Table 6 presents the lifetime gas consumption and pollutant emissions. They are calculated for the new passenger cars registered in Beijing in 2011 and 2012. Row 2 suggests that Beijing’s vehicle lottery policy reduced fuel consumption by $1.48 \times 10^{10}$ liters, a decline of approximately 46.65%. Similarly, the emissions of each pollutant were reduced by 46.65% with vehicle restriction.

Table 6: Policy Effects on Gas Consumption and Pollutant Emissions in 2011 and 2012

<table>
<thead>
<tr>
<th></th>
<th>Without VLS</th>
<th>With VLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales of new passenger cars</td>
<td>1,700,449</td>
<td>864,634</td>
</tr>
<tr>
<td>Gasoline consumption (liters)</td>
<td>$3.18 \times 10^{10}$</td>
<td>$1.70 \times 10^{10}$</td>
</tr>
<tr>
<td>CO$_2$ emissions in tons</td>
<td>$7.45 \times 10^7$</td>
<td>$3.98 \times 10^7$</td>
</tr>
<tr>
<td>PM$_{10}$ emissions in tons</td>
<td>889.81</td>
<td>474.69</td>
</tr>
<tr>
<td>NO$_x$ emissions in tons</td>
<td>$14.02 \times 10^4$</td>
<td>$7.48 \times 10^4$</td>
</tr>
<tr>
<td>CO emissions in tons</td>
<td>$1.90 \times 10^6$</td>
<td>$1.01 \times 10^6$</td>
</tr>
</tbody>
</table>

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 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 $Q_{mt}^0$ and $Q_{mt}^1$ be the total sales product $j$ in market $m$ at time $t$ under VLS and no VLS, respectively. $r_{jmt}^0$ and $r_{jmt}^1$ are the relative market shares of product $j$. The change in gas consumption is given by

$$
\Delta \text{GAS}_{mt} = \sum_{j \in J_{mt}} Q_{jmt}^0 \cdot VMT \cdot FC_j \cdot 15 - \sum_{j \in J_{mt}} Q_{jmt}^1 \cdot VMT \cdot FC_j \cdot 15
$$

$$
= 15 \cdot VMT \cdot \left[ \sum_{j \in J_{mt}} Q_{mt}^0 \cdot r_{jmt}^0 \cdot FC_j - \sum_{j \in J_{mt}} Q_{mt}^1 \cdot r_{jmt}^1 \cdot FC_j \right]
$$

$$
= \left[ -15 \cdot VMT \cdot (Q_{mt}^1 - Q_{mt}^0) \cdot \sum_{j \in J_{mt}} r_{jmt}^1 \cdot FC_j \right] + \left[ 15 \cdot VMT \cdot Q_{mt}^0 \cdot \sum_{j \in J_{mt}} (r_{jmt}^0 - r_{jmt}^1) \cdot FC_j \right]
$$

where the first term represents the effect on gasoline consumption due to car sales decrease alone, whereas the second term measures the impact on gasoline consumption because
of changes in fleet fuel efficiency. In our analysis, VLS would have reduced the gas consumption by 51.62% in Beijing in 2011 and 2012 holding fleet fuel efficiency constant, while changes in fleet fuel efficiency increased fuel consumption by 4.96%.

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 car sales, fleet composition, fuel consumption, and pollutant emissions. 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 results suggest that Beijing’s VLS helped at limiting new vehicle sales and at reducing gasoline consumption and air pollution. However, vehicle fleet composition changed due to the VLS, shifting it towards less fuel efficient cars. This change can undermine the potential benefits of the VLS.

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 can be an effective approach for controlling vehicle growth and vehicular environmental issues, but it hinders fleet fuel efficiency due to its impact on fleet composition. As a result, VLS could still be improved by setting quotas for fuel efficiency categories or engine size categories.
References


Appendix A

Table 1: City Characteristics in Beijing, Nanjing, Shenzhen, and Tianjin

<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.