

Vehicle Quota System and Its Impact on the Chinese Auto Markets : A Tale of Two Cities

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Abstract

This paper investigates the impact of the vehicle quota system of Shanghai, China, on two Chinese passenger vehicle markets. The empirical findings suggest that, conditional on purchase of a license in a quota system, consumers intend to purchase more expensive high-end vehicles since the customers who can afford the license are less price-sensitive. Hence, this system puts manufacturers of low-end cars at a disadvantage. A simulation of the vehicle registration tax system of Hong Kong shows that a progressive tax system is as effective as the quota system in vehicle control but also is able to protect the indigenous brands.

Keywords: Chinese auto industry, Vehicle quota system, counterfactual analysis, discrete choice model

JEL Classification: C25, H11, L16

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[Shanghai license plates auctions]... is a good example of the sometimes unintended consequences of an economic policy. On the one hand, fewer cars are on the road. On the other hand, the cars that are on the road are bigger and less fuel-efficient.

–*China's Economic Supertrends* by Jason Inch

1 Introduction

The Chinese auto market has developed rapidly since the early 1990s, and further accelerated after China's entry into the World Trade Organization in 2001. However, ancillary facilities, such as parking lots¹ and road capacity are not ready to support such rapid development, which has led to serious traffic congestions in cities such as Beijing and Shanghai. In addition, China has become the world's largest auto market which has created some other serious problems such as air pollution and energy shortages. To control the vehicle population and thereby resolve these problems, the Chinese central government has applied tax policies such as a fuel tax and a consumption tax, which have proven to be effective in controlling emissions (Xiao and Ju, 2013). Some local governments have implemented more stringent policies. For example, Beijing applied the odd-even license plate rule,² while Shanghai, the largest city by population in China, imposed a vehicle quota system (VQS) and allocated the quota through auction. Such innovative policies could be good models for other emerging economies facing similar situations.

The effectiveness of the VQS seems evident, but its success has never actually been fully measured. Previous studies on a similar VQS in Singapore suggest that it is effective in vehicle control. However, they cannot disentangle the effect of VQS from other factors such as the economic situation (Seik 1998) or conditions of the options to purchasing a vehicle, which may include the improvement of public transportation or increasing traffic congestion.

¹For example, Beijing had parking space for 1.3 million vehicles by the end of 2010 when the city had about 5 million cars. (Beijing's Parking Problem, *China Daily* 04/02/2011 page 5)

²The regulation was introduced on July 20, 2008, to ease congestion and reduce pollution during the Olympics and Paralympics. It limited the city's 3.3 million private cars to alternate days on the road, according to whether they had even- or odd-numbered license plates.

So, the effect of VQS on vehicle control may not be that obvious.

The influence of the VQS on consumers' vehicle choices is even more ambiguous and controversial. On the one hand, as the number of licenses sold nears the quota and licenses become expensive, low-income (or price-sensitive) customers drop out by self-selection. High-income customers are less sensitive to these prices and intend to purchase high-end vehicles; this may shift overall consumer demand in favor of high-end cars (Koh 2003). On the other hand, a license is a perfect complement to the vehicle. Due to their personal budget constraints, consumers may choose a low-end vehicle to compensate for their expenditure on the license. This is the income effect of the quota auction. The overall effect is ambiguous (see Section 4.1 for details). It is important to quantify this effect, since consumer demand will determine the competition structure among automakers. In particular, when manufacturers focus on a specific product category, the demand for that product will influence their choices of product quality.

This paper investigates the impact of Shanghai's VQS on new vehicle sales, consumers' choices and manufacturers' competition structure in the passenger vehicle market. First, we compare the sales of passenger vehicles and their price distribution using registration data for Shanghai and Beijing, cities with similar average income levels. The empirical findings show that sales in Shanghai are much lower and skews toward high-price/high-quality cars. The average price of cars sold in Shanghai is about RMB 28,000 (USD 7,000) higher than in Beijing. This could be caused by differences in demographics such as income or household size, or the dominance of the self-selection effect of the quota auction. Second, to identify the effect of VQS, we apply methodology from Berry, Levinsohn and Pakes (1995, hereafter BLP) to the car registration data for these two cities and estimate consumer preference over some key features and prices of cars. Using the model estimates, we simulate some counterfactual scenarios. The comparative statics between scenarios suggest that removal of the license quota in Shanghai would increase new car sales by 74%, so the license quota is effective in controlling the vehicle population. However, consumer preference in Shanghai also plays a significant role, with car buyers placing a lower value on owning a vehicle. The skewed price distribution toward high-end products is because only less price-sensitive (high-income) consumers will choose to buy. This decreases the demand for and the market share of indigenous brands,

that targets the low-end market.

Most previous research on license quota studies the VQS in Singapore (Koh 2003, Koh and Lee 1994), which is different from our study in the following aspects. First, the Singapore quota is valid for 10 years while the Shanghai quota is for lifetime of the owner, and thus the lump-sum price can be regarded as part of the vehicle cost. Second, there are five categories by car type and cylinder size in Singapore's VQS (Chu, Koh and Tse 2004), and each category has a separate quota, so lower-income motor vehicle buyers do not have to bid against wealthier motor vehicle buyers for licenses (Tan 2003). But Shanghai's quota system gives an overall quota for licenses and does not categorize cars. Because of this, low-income consumers may be crowded out as the license price increases. This shifts the income distribution of vehicle consumers toward the high-income group. Gertler, Locay, and Sanderson (1987) show that high-income consumers may prefer high-quality/high-price to low-quality/low-price options, while low-income consumers are the opposite; therefore, such a change in income distribution will change the demand structure and the competition structure among manufacturers.

Little research has studied the effect of the quota system on the competition among manufacturers. Koh (2003) finds that the VQS benefits distributors of large luxury cars since the license premium forms a relatively smaller percentage of the total price of a luxury car than a smaller car. Similarly, previous research on trade suggests that quantitative import restrictions shift the composition of imports in favor of relatively more expensive items within the quota-constrained import category (Aw and Roberts 1986, Falvey 1979, and Feenstra 1988). The quantitative restraint raises the import price, which makes consumers reduce the quantity they purchase but raise the quality. However these findings are based on the assumption that license is free. If the license becomes expensive, the consumer may offset some of that cost through substituting smaller cars in place of luxury cars. In light of this substitution effect, this paper applies counterfactual analysis to study the effect of the VQS on different types of manufacturers.

This paper contributes to the literature in the following aspects. First, it empirically tests the effect of quotas on vehicle choice. Our empirical findings show that the average vehicle price in Shanghai is RMB 28,000 higher than that in Beijing. Second, this paper further analyzes the

factors contributing to the difference in price. Our empirical results suggest that consumers who choose to buy cars under the Shanghai VQS have higher incomes than car consumers in Beijing, which shifts their demand toward high-price products. The political implication of such findings is that some policy changes, such as removal of the VQS, will affect consumers' choices. Third, this paper disentangles the role of the VQS from other factors in vehicle control, such as the intrinsic preference to purchasing a private vehicle. We find that the VQS is an effective instrument in quantitative restraint; however, the lower value of local intrinsic preference to cars in Shanghai plays a more significant role in vehicle control. Finally, this paper studies the impact of quotas on the competition structure of passenger vehicle manufacturers in China. In particular, we find that the market shares of indigenous brands shrink while those of the joint ventures with larger foreign automakers expand as the licenses become expensive. Our analysis shows the policy conflicts between central government and local governments: the central government has shown its support for indigenous automobile brands,³ but local government policy may eventually undermine the advantage of indigenous brands.

The rest of the paper is organized as follows. Section 2 briefly reviews the history of the license auction system, the market structure of the Chinese passenger vehicle industry and the preliminary findings of the influence of the VQS on the market structure. Section 3 introduces the data. Section 4 describes the empirical model, and Section 5 describes the estimation method. Section 6 shows our empirical results. Section 7 presents our empirical findings of counterfactual analyses. Finally, Section 8 concludes the paper.

2 Auto Manufacturers and the License Quota

2.1 Auto manufacturers

Chinese manufacturers of passenger vehicles can be categorized into two different types: indigenous-brand manufacturers, such as BYD, Geely, and Chery, and joint ventures between

³In a draft catalog of car models for government procurement released by the Ministry of Industry and Information Technology in March 2012, only domestic car models were included.

local manufacturers and foreign car makers such as Shanghai Automotive Industrial Corporation (SAIC) with Volkswagen and General Motors (GM), Beijing Automotive Investment Company (BAIC) with Hyundai, and Dongfeng with Honda.⁴ Indigenous-brand manufacturers are usually independent and owned by private companies or local governments, and their products are mainly low-end small cars. Their market shares are relatively small. Joint ventures, on the other hand, hold relatively new technologies, so most of their products are medium- to high-end. Currently, joint ventures dominate this industry, but indigenous brands are expanding rapidly. In 2009, sales from joint ventures accounted for 67.5% of the passenger vehicle sales in the Chinese market, while indigenous brands accounted for 32.5% of total sales. The market share of local brands increased by 6.6% over 2008.⁵ As their sales have expanded rapidly in recent years, they are playing a more significant role in China's market.

2.2 Brief history of the license-plate auction

Since Shanghai issued its first private car license plate in 1986, eight years after the start of the Chinese economic reform, the city has been trying to control the number of private cars using its limited road system. In 1994, the local government started to set a quota on newly issued licenses, selling them in a sealed bid reserve price auction.⁶ From 1994 to 1999, only 11,000 licenses were sold in this way. In 2000, Shanghai Municipal People's Congress issued the Regulations of Motor Vehicles in Shanghai, which opened the auction to not require a reserve price. As the demand for private cars soars, the price of license plates increased dramatically (see Figure 1).

The regulations were replaced by the Law of the People's Republic of China on Road Traffic Safety on May 1, 2004. In the same month, the Assistant Minister of Commerce announced that the license auction in Shanghai violated the law, and the rumor of quota cancellation

⁴Due to the lack of technology, some local firms merged their indigenous-brand plants into their joint ventures with foreign partners. Therefore, although most joint ventures only produce car models of their foreign partners' brands, some joint ventures also produce indigenous-brand models (e.g., FAW).

⁵China Auto Industry Development Annual Report 2010.

⁶The first auction for the plates was hold at the Shanghai Center July 18, 1992, and the winning bid for the first plate was RMB 305,000 *yuan* (or USD \$ 55,860). At this auction, 14 plates were sold. Different from the current auction to fill the quotas, the bidding items are specific license numbers.

spread. The price of licenses dropped dramatically from RMB 44,200 to 10,800 in that month. Since then, the debate continued on whether the license auction should be canceled, while license prices have been rocketing upward. Overwhelming criticism of the rapidly growing price forced the government to adjust the auction rule in January 2008, which lowered the price temporarily.

At present, the auction is scheduled on the third Saturday of every month and its procedure consists of two steps. First, all bidders must register before the bidding day, and pay RMB 2,000 as a nonrefundable deposit. Second, on the auction day, there are two separate bidding periods. During the first bidding period, from 10AM to 11AM, all bidders have one hour to submit a bid; otherwise, they have to withdraw from the auction. During the second period, from 11:00AM to 11:30AM, they have 30 minutes to enter two higher bids that are restricted to some interval above the lowest bid. All bids can be submitted by phone or the Internet. This mechanism can guarantee that customers who are willing to pay high enough will get the license. They can bid their willingness-to-pay in the first period so that they do not need to bid in the second period, their bid will automatically increase up to the amount they are willing to pay. Or, they can bid the upper bound of the interval in the second period. Therefore, the steady price increase indicates some reasons why the demand for the license quota has shifted up.

2.3 Secondhand market and other options

The license is transferable through the secondhand market, but this can push the license price up even further.⁷ The monthly transaction volume in this market is about half of the newly released quota. Usually, the transaction price is higher than the average auction price. In recent years, scalpers have controlled market, pushing the price gap between second hand market and the auction market to expand from a few hundred in 2010 to over RMB 5,000 yuan in January 2013.⁸ This is actually the market clearing price, since consumers who lose

⁷Krishna and Tan (1999) show that the price of transferable licenses tends to be higher than the price of an otherwise identical nontransferable license, when the quota is very restrictive.

⁸No policies have proven effective in preventing scalpers from getting involved in the city's monthly auction. A new policy was introduced in July 2012 to rein in price speculation. The rule, which extends the period motorists must keep a license

in the auction can buy a license in this market as long as their willingness to pay is higher than the transaction price. So, the quantitative constraint becomes soft due to the existence of the secondhand market.

As an alternative to paying for an expensive Shanghai plate, drivers in the city have been buying license plates from the neighboring province. However, some local traffic regulations make this option less attractive. During rush hour,⁹ vehicles without local license plates cannot drive on the flyovers in the city, which significantly increase driving time.¹⁰ Also, the annual vehicle inspection must be done where the vehicle is registered, which is an inconvenience to drivers registered in other cities. Therefore, the licenses of the other provinces are not an effective substitute for Shanghai licenses.

2.4 Preliminary findings

We contrast the vehicle sales distribution of Shanghai to that of Beijing to disentangle the impact of quota auctions on the competition among manufacturers. These two metropolises are similar in many ways. Beijing is the political center of China and the economic center of northern China, while Shanghai is the economic center in eastern China. As shown by Table 1, the two cities are very similar in average income, average savings, number of households, and average number of people in a household. The main difference between them is that the area of Beijing is about 2.6 times that of Shanghai.

According to Table 2, the number of cars sold in Beijing was about five times the number of cars sold in Shanghai in 2010, so the quota system has been effective in vehicle control.¹¹ Another difference between these two cities is that the average price of a vehicle in Shanghai is about 28% higher than the average price in Beijing. We test the hypothesis that the average price of car models registered in Shanghai is higher than that in Beijing, and the empirical results show that we cannot reject the null hypothesis. Moreover, Figure 2 shows that the

plate from one year to three years, is intended to deter scalpers from reselling licenses. But since the policy was introduced the average price of a Shanghai license plate has increased more than 28% due to the overwhelming demand.

⁹The rush hours are 07:30-09:30 and 16:30-18:30 from Monday to Friday.

¹⁰A fine of 200 yuan applies for violations.

¹¹Given that the license is transferable, the effective mechanism of the quota system is the increasing license price.

vehicles price distribution for Shanghai lies to the right of that for Beijing, implying that the share of cars with a price higher than any given price is larger in Shanghai than in Beijing. Given the fact that indigenous brands usually produce low-end vehicles, while joint ventures produce high-end cars, such a result implies that the quota system is likely to benefit the joint ventures.

However, the price difference could be attributed to other factors such as difference in product quality, choice set, competition structure and consumer preference. Without controlling for these factors, we cannot identify the impact of the quota system on car sales. To take into account these factors, we apply the revealed preference method similar to the BLP (1995) framework to investigate the impact of license prices on auto market competition.

3 Data description

3.1 Auto Data

Our data record the monthly new vehicle registration information of each car model at province level in 2009 and 2010.¹² During the sample periods, Shanghai is the unique city that has license quotas, which are sold by auction. The difference in sales distribution of the new vehicles between Shanghai and the other provinces, therefore, allows us to investigate the influence of license price on vehicle control and the market structure. This is a unique feature of this data set. Previous research about Singapore's VQS lacks economic counterparts that could be used as a control group, so its impact on market structure is unidentifiable.

The data set includes variables identifying the registration location of a new car (e.g., Pudong district in Shanghai), registration time (e.g., June 2010), model number, model name, brand, firm, origin of brand, and purpose of usage (private or business). We further collected car features from the monthly magazine Autocar and auto.sohu.com. The prices are manufacturer

¹²Data are obtained through private arrangement. To protect the proprietary information of the data provider, we cannot release the data source.

suggested retail prices (MSRP) of the base model among all the models with the same name-plate available in the market. Physical characteristics include dimensions (width and length), engine characteristics (horsepower and displacement), and performance measures (fuel consumption). We also obtain the average monthly license price of the vehicle quota auction in Shanghai published online.

We drop the registration information for business-use cars since business consumers are quite different from private consumers. We also drop observations of Shanghai in December 2010, since the price of licenses is abnormally low in that month due to some technical errors. Observations with monthly sales of less than five in a market are also dropped. Since the quota system only applies to consumers in urban districts, not to those in the suburban districts, and the household incomes are quite different between urban and suburban areas, we use registration information for only the urban districts.¹³

There are 484 different car models sold in 2009 and 2010 as shown in Table 3. These car models can be categorized into five segments: mini, small, intermediate, large, and luxury.¹⁴ The number of models in each of these segments is mini, 37; small, 149; intermediate, 206; large, 26; and luxury, 66. The geographic market is defined as the whole metropolis. The number of observations at model-market-month level is 10,534.

3.2 Demographic data

Consumers with different incomes usually have heterogeneous preferences, so we need to control for income. Unfortunately, we do not have individual-level income data. From the Shanghai/Beijing Statistical Yearbook, we can obtain the annual average income of each quantile. Following BLP (1995), we assume the income distribution to be lognormal; then, we estimate the standard deviation and mean of the lognormal distribution in the following way. We first simulate 10,000 samples that are lognormal distributed with standard deviation a and mean b .

¹³For Shanghai, the urban districts include the following: Baoshan, Changling, Hongkou, Huangpu, Jing'an, Luwan, Putuo, Pudong, Xuhui, Yangpu, Zabei, and Minhang; for Beijing, urban districts include Chanping, Caoyang, Congwen, Daxing, Dongcheng, Fangshan, Fengtai, Haidian, Shijingsan, Shunyi, Tongzhou, Xicheng, and Xuanwu.

¹⁴See Appendix for segmentation definition.

We compute the mean of each quantile of the simulated sample, and match it to the average of each quantile of the observed income. We calculate the sum of squares of the difference between the two. Finally, we search for the optimal a and b that minimize this summation for each metropolitan city in each year. Finally, the simulated individual incomes are randomly drawn from the distribution with the optimal parameters.

According to China Household Finance Survey in 2011, less than 10% of car purchasers get a car loan,¹⁵ which means most consumers use their savings to purchase a car. Hence, the feasible choice set is subject to the consumers' budget constraint. We assume that a consumer i can only afford a car j whose price, p_j , is no greater than her savings, $Savings_i$. If $Savings_i < p_j$, then product j is not in the feasible set of consumer i . In the other words, the feasible set of consumer i is the set of products: $\{j \mid Savings_i < p_j\}$. We assume the savings of consumer i is proportional to her income y_i . That is to say, $Savings_i = y_i \cdot AverageFamilySize \cdot \frac{AverageSavings}{AverageIncome}$. Both the average family size, $AverageFamilySize$, and the average saving ratio, $\frac{AverageSavings}{AverageIncome}$, are computed from the Shanghai / Beijing Statistical Yearbook.

4 Model

4.1 Theoretical framework and illustration

Taking into account consumers' budget constraints and product heterogeneity, we assume that the indirect utility function of consumer i purchasing car j is given by,

$$u_{ij} = \beta q_j + \alpha (\log(y_i) - \log(p_j + p_l)), \quad (1)$$

where, q_j is the product quality and y_i is the savings of individual i .

This utility function is composed of two parts: the utility from consumption of good j (quality) and the utility from consumption of other complex goods using the residual income. There

¹⁵In contrast, this number is up to 70% in the United States.

are two features of this indirect utility function: first, the marginal rate of substitution of complex goods for vehicle quality, $MRS_{jy} = \frac{\frac{\partial u}{\partial(y-p)}}{\frac{\partial u}{\partial q}} = \frac{\delta}{\alpha} \frac{1}{(y-p)}$, increases as vehicle price increases, meaning that consumers must give up more complex goods for high-end cars. Second, the MRS_{jy} decreases when consumers' savings increase. Hence, consumers with higher income are more likely to choose high-quality/high-price vehicles, while the low-saving consumers will choose the low-quality/low-price vehicles, as illuminated by Gertler, Locay and Sander-son (1987).

As shown in Figure 3, there is a choice between the high-quality/high-price bundle (p_h, q_h) and low-quality/low-price bundle (p_l, q_l) . For low-income individuals, their choice is between A and B. The marginal utility of car quality is relatively low, so they prefer low-quality to high-quality cars. Hence, bundle B (p_l, q_l) will be chosen. As the quota license becomes expensive, self-selection drives out low income consumers. High-income individuals will choose between options C and D. Their marginal rate of substitution of complex goods (residual income) for car quality decreases; hence, bundle C (p_h, q_h) will be chosen. However, if the price of the quota license increases so much that the residual income is changed from Y to Y' , then the choice is between E and F. Again, bundle F (p_l, q_l) will be chosen. Therefore, the impact of the quota license auction on vehicle choice is ambiguous.

4.2 Empirical specification

Assume that consumers are heterogeneous in household income and idiosyncratic tastes. Then the indirect utility of consumer i purchasing product j from segment g in market m at time t is given as follows:

$$\begin{aligned}
u_{ijmt} &= \alpha \ln(y_{imt} - p_{jmt}) + \delta_{jmt} + \zeta_{igmt} + (1 - \sigma)\epsilon_{ijmt} \\
&= \alpha \ln(y_{imt} - p_{jmt}) + \beta_0 + \beta X_j + \beta_{sh} D_{-SH}_{jm} + \beta_{bj} D_{-BJ}_{jm} \\
&\quad + \beta_Y D_{-year}_t + \beta_M D_{-month}_t + \beta_{BJ} D_{-BJ}_m + \beta_{BO} D_{-BO}_j + \zeta_{jmt} \\
&\quad + \zeta_{igmt} + (1 - \sigma)\epsilon_{ijmt},
\end{aligned}$$

where α is the price coefficient; p_{jmt} is the total payment for product j in market m (a summation of car price and license fee where applicable), and it is time variant; and δ_{jmt} is the mean utility of product j in market m at time t . We further parameterize the mean utility as a function of product features, assuming these features will generate the same utility to all the consumers. Specifically, X_j is a vector of product characteristics, including height, length, weight, fuel consumption and horsepower. For a given product model, such features are time and market invariant. D_SH_{jm} is a dummy variable equal to 1 if product j is produced and sold in Shanghai ($j \in m = Shanghai$); similarly, D_BJ_{jm} is a dummy variable equal to 1 if product j is manufactured and sold in Beijing ($j \in m = Beijing$). Therefore, the coefficients of these two terms reflect consumers' preference to the local product. D_year_t , D_month_t and D_BJ_m are dummy variables for year (baseline is 2004), month (baseline is January), and market (= 1 if $m = Beijing$), respectively. Here, the market is defined at the city level. The coefficient for the city dummy measures the intrinsic vehicle preference of consumers in Beijing relative to that of consumers in Shanghai. The dummy vector D_BO_j is four-dimensional, indicating the geographic origin of product j 's brand. Each dimension of the vector is a binary variable, equal to 1 if the brand origin falls in the corresponding country/area, including America, Europe, China and Japan. The baseline of the brand origin dummy vector is Korea, corresponding to the zero vector. ξ_{jmt} is a quality index capturing all the other features, which are observable to the consumers but unobservable in our data. We assume this variable follows a mean zero distribution. ζ_{igmt} is a nested logit random taste that is constant for products in the same segment. σ is the nested logit parameter, $\sigma \in (0, 1)$, measuring the correlation of consumers' preference over the within-segment products: the correlation goes to one as σ approaches one. And ϵ_{ijmt} is the consumer-specific deviation from the mean utility. In the model, we denote $\theta = (\alpha, \sigma, \beta)$ as the set of demand parameters to be estimated.

Consumers will choose a product to maximize their utility. If they choose to buy a product, they may choose from the data set. If they choose not to buy or to buy some products outside, we treat this as an outside option and standardize the mean utility to be $\delta_{i0mt} = 0$ for all individuals, so the utility of the outside option is given by,

$$u_{i0mt} = \alpha \ln(y_{imt}) + \xi_{0mt} + \zeta_{igmt} + (1 - \sigma)\epsilon_{i0mt}.$$

Based on BLP (1995), the above specifications imply that the product demand in terms of market share can be described by a random coefficient nested logit model as follows:

$$S_{jmt} = \int s_{ijmt}(y_{imt}) dy_{imt} = \int \frac{e^{\delta_{ijmt}/(1-\sigma)} \cdot 1(y_{imt} \geq p_{jmt})}{D_{igmt}^\sigma \sum D_{igmt}^{1-\sigma}} dy_{imt}, \quad (2)$$

where $D_{igmt} = \sum_{k \in g} [e^{\delta_{ikmt}/(1-\sigma)} \cdot 1(y_{imt} \geq p_{kmt})]$ is the inclusive value of all the products within segment g in the feasible set of consumer i in the market m at time t . As shown by equation 2, the aggregate market share is the integration of individual market shares over income distribution.

5 Estimation

5.1 Identification method

By matching the observed market shares and predicted market shares in equation (2), we can estimate the model parameters. Since integration is not feasible, the integral is approximated by the following equation,

$$S_{jmt} = \frac{1}{ns} \sum_{y_{imt}} s_{ijmt}(y_{imt}) = \frac{1}{ns} \sum_{y_{imt}} \frac{e^{\delta_{jmt}/(1-\sigma)} \cdot 1(y_{imt} \geq p_{jmt})}{D_{igmt}^\sigma \sum D_{igmt}^{1-\sigma}} \quad (3)$$

where, y_{imt} is a random draw from lognormal distributions with estimated parameters obtained by the approach described in Section 3. We set the number of random draws ns to be 2,000.

Following Nevo (2000) and BLP (1995), we use a three-step method to estimate the model parameters. First, for each value of the random coefficient (α) and nested logit parameter (σ), we estimate the mean utility δ_{jmt} using a contraction mapping method. We update δ_{jmt} to match the predicted market shares with the observed market shares by iteration, until the changes of δ_{jmt} meet the tolerance criteria: the maximum difference between two consecutive sets of δ is less than 10^{-9} , and the average difference is less than 10^{-10} . Second, we estimate

the parameters in the mean utility with the generalized method of moments. Formally, the moment conditions are given by,

$$E[\delta(\alpha, \sigma) - x^d \beta | z^d] = 0,$$

where x^d is a vector of all variables in the mean utility function; z^d is a vector of variables which are mean independent of unobserved product characteristics, ξ . Given that the price and within-group market shares are correlated with unobservable characteristics and, so, endogenous, we need instrumental variables for the moments. We discuss this in the next section. Finally, we search for the optimal values of random coefficients (α and δ) to minimize the following objective function,

$$m'(\theta) W m(\theta), \tag{4}$$

where, $m(\theta)$ is the moment condition and W is weighting matrix.

5.2 Instruments

The prices and the within-group market shares are endogenous variables, which calls for instrumental variables (IVs) for the moment conditions. We apply two sets of IVs to our estimation.

The first set of IVs consists of variables measuring the exogenous product attributes. The instruments along this line include the products' own observed characteristics, such as height, length, weight, fuel consumption, and horsepower, the sum of characteristics of the other products within the same segment and produced by the same firm, and the sum of characteristics of products within the same segment but produced by the other firms. BLP (1995) suggest that these are optimal instruments since they enter the pricing equation derived from the first-order condition of the profit maximization problem.

The second set of IVs is the number of markets, defined at the city level, in which a car model has presence. Entrance to multiple markets may lower the city-level costs, such as advertisement expenditures. Hence, the number of markets is correlated with price and independent of

the unobservable product characteristics, making it a valid instrument.

6 Estimation Results

6.1 Parameter Estimation

The demand parameter estimates are presented in Table 4. Model (i) is standard logit model without control of within-group correlation between alternative choice options. Model (ii) to (iv) are nested logit models: model (ii) does not take into account the endogeneity problem, while model (iii) does. Model (iv) is the full model taking into account both the endogeneity problem and budget constraint.

The main difference between models (i) and (ii) lies in the price coefficient: the coefficient in the nested logit model is more than three times that in the logit model, meaning that consumers are actually more price sensitive taking into account the within-group correlation. When consumers' preference over options in the same segment is correlated, a price drop of any car will attract demand from the other cars, leading to a higher price elasticity. The price coefficient in model (iii) becomes bigger in absolute value after controlling for the endogeneity problem because the unobservable characteristics are positively correlated with the price, which will offset the negative price effect on the market share, and hence underestimate the impact of price on consumers without controlling the endogeneity. The estimates of within-group correlation are similar between models (ii) and (iii), 0.6 approximately. It indicates that consumers' preference over car models within the same segment is highly correlated.

Our full model takes into account consumer heterogeneity in incomes. This model is superior to the other models in that it controls for both the endogeneity problem and budget constraint, so we will use the empirical results from this model for further analysis.

The income coefficient is positive and significant, meaning that the wealth effect is positive to the consumer utility. Table 5 summarizes the corresponding price elasticity computed using

the estimated price coefficient given by,

$$\frac{\partial s_j}{\partial p_k} \frac{p_k}{s_j} = \begin{cases} -\alpha \frac{p_k}{s_j} \frac{1}{ns} \sum_{y_i} \frac{1(y_i \geq p_j)}{y_i - p_j} s_{ij} \frac{1 - \sigma \bar{s}_{ij/g} - (1 - \sigma) s_{ij}}{1 - \sigma} & \text{if } j = k, \\ \alpha \frac{p_k}{s_j} \frac{1}{ns} \sum_{y_i} \frac{1(y_i \geq p_j)}{y_i - p_j} s_{ij} \frac{\sigma \bar{s}_{ik/g} + (1 - \sigma) s_{ik}}{1 - \sigma} & \text{if } j \neq k, j, k \in g, \\ \alpha \frac{p_k}{s_j} \frac{1}{ns} \sum_{y_i} \frac{1(y_i \geq p_j)}{y_i - p_j} s_{ij} s_{ik} & \text{otherwise.} \end{cases} \quad (5)$$

Table 5 shows that the average monthly model level elasticity is -4.3583 and the range of variation is not big. Consumers are heterogeneous in their incomes, and so are their price elasticities. Everything equal, high-income customers are less price sensitive, which could be observed in equation (5). The cross elasticity is much smaller in magnitude, which is reasonable given that the time period is only a month and the number of competitors is large.

The parameters of car characteristics are of the expected sign. Consumers prefer large (wide and long), powerful but fuel efficient cars. These results, together with the estimate of within-group correlation, coincide with Deng and Ma (2010).

Brands produced locally are also preferred: the probability that a consumer will purchase a locally produced brand, no matter whether it is a foreign brand made by joint ventures or an indigenous brand, is 48.74% ($\exp(0.397) - 1$) higher than the probability of purchasing a non-local brand in Beijing. For Shanghai, that probability is 13.43% ($\exp(0.123) - 1$) higher. Two possible reasons could explain this findings: first, it is easier to get access to spare parts or services for local brands; second, local residents may have intrinsic preference for the local brands.

The coefficients of origin-of-brand dummies show that consumers prefer European (such as Volkswagen and Audi) and Japanese (such as Honda and Toyota) cars to Korean ones (such as Hyundai); consumers are indifferent between American cars (such as Ford and GM) and Korean cars. Indigenous brands are the least preferred.

The dummy for Beijing is significantly positive (0.746), implying that the purchase probability in Beijing is 2.1085 times that in Shanghai. In other words, the intrinsic preference for cars is higher in Beijing. The possible reasons behind this may be the following: First, public

transportation in Shanghai is more convenient. The length of metro lines in Shanghai is 35% more than in Beijing (as in Table 1). Given that the area of Shanghai is less than half that of Beijing, this means the metro network is much denser in Shanghai.¹⁶ Second, since the area size of Shanghai is smaller, commuting distance could be lower in Shanghai, and so driving is less necessary. Third, as shown in Table 6, there are 93 more car models available in Beijing, and their average price is RMB 20,000 lower than the average of the sample mean. These low-end cars enlarge the choice set for marginal consumers, which encourages purchase. In contrast, Shanghai only has two unique car models, with much higher prices than the average.

6.2 Consumer income distribution

Using the estimated parameters, we can estimate consumers' average income conditional on purchase given by,¹⁷

$$\begin{aligned}
& \sum_{i=1}^{ns} y_i \cdot \Pr(\text{income is } y_i \mid \text{consumer } i \text{ purchases a car}) \\
= & \sum_{i=1}^{ns} y_i \cdot [\Pr(\text{consumer } i \text{ purchases a car} \mid \text{income is } y_i) * \Pr(\text{income is } y_i)] \\
& / \Pr(\text{consumer } i \text{ purchases a car}) \\
= & \frac{1}{ns} \sum_{i=1}^{ns} y_i \cdot \tilde{s}_{ij} / \sum_{j=1} \tilde{s}_{ij},
\end{aligned}$$

where \tilde{s}_{ij} is the estimated market share of car j purchased by a consumer i with income y_i .¹⁸

The last equality follows Bayes' rule and the fact that $\Pr(\text{income is } y_i) = 1/ns$ since we make ns random draws from the income distribution.

¹⁶A significant portion of license auction revenue has been spent on the construction of public transportation, like subways, in Shanghai.

¹⁷When we estimate the model parameters, we convert incomes into savings using different saving rates of these two cities (shown in Table 6), obtained from the statistics yearbook. Since this is a linear transformation, the estimated market shares for each saving rate also matches the corresponding income.

¹⁸We drop the subscript for market and time for the moment.

Tables 7 and 8 show the estimated average income of car buyers (column i). The average in Shanghai is RMB 20,000 higher than in Beijing. Given that the difference in income between Shanghai and Beijing is less than RMB 2,000 as shown in Table 1, these results imply that high license price has driven out the low-income customers and skewed the income distribution to the high end. Since high-income consumers are less price-sensitive, they are more likely to choose expensive cars, which will move the price distribution of vehicles in Shanghai to the right.

The difference in consumers' income, induced by VQS, itself may not be able to shift the price distribution to the extent observed. Other factors, such as the market structure and difference in consumers' intrinsic preference for vehicles, will also influence consumers' choices. For example, Table 6 shows that over 90 car models are not observed in Shanghai.¹⁹ If they are not available and so are not in the consumers' choice set, then consumers have to choose more expensive cars. To identify the impact of VQS, we will conduct some counterfactual analysis.

7 Empirical findings of counterfactual analysis

7.1 Car sales and price distribution

We estimate car sales, price distribution and market shares for different types of manufacturers in four counterfactual scenarios. First, we remove the license fee in Shanghai. Second, we include the models unique in Beijing to the Shanghai market while removing the license fee. Third, we add to the second scenario, by setting the intrinsic preference to vehicles in Shanghai to match that in Beijing. Finally, we assume Beijing adopts VQS. The final scenario will be used as contrast.

Since the total sales of Beijing and Shanghai constitute a small portion of Chinese national sales (10.36% in 2010), we assume the VQS does not affect the national car prices significantly. Given that the utility function is monotonic in the total payment, addition of a license

¹⁹We cannot identify whether this is due to unavailability of the car models or due to no sales.

fee does not change the ranking of cars, but it does shrink the choice set of cars that a consumer can afford.

We use the observations and estimated utility of June 2010 in Shanghai for our counterfactual simulation. Sampling with replacement, we make 50 random draws of the income y_{imt} and idiosyncratic error term $\zeta_{igmt} + (1 - \sigma)\varepsilon_{ijmt}$, and combine them with the estimated mean utility ($\hat{\delta}_{ijmt}$), price coefficient ($\hat{\alpha}$), and total payment p_{jmt} (license fee may be included), to compute the indirect utilities of the products, u_{ijmt} . Consumer i is assumed to choose the product with highest utility, subject to her budget constraint. In this way, we can find the optimal choice of individual i and the corresponding probability of incidence and the product price, p_{jmt}^* . By aggregating the choice probability for the same product over individuals, we derive the market share for each product. After ordering the product in price and calculating the cumulative density function (CDF) of price, we plot the price distribution for scenario 1 in Figure 4.

Based on consumers' decision whether or not to purchase a vehicle at the null scenario, we categorize consumers into two groups: buyers and nonbuyers. We depict the price distribution of buyers at null scenario as cdf1, and the price distribution of these two groups of consumers at the counterfactual scenario as cdf2 (incumbent buyers) and cdf3 (new entrants induced due to removal of the license fee). It is evident that the cumulative distribution of incumbent buyers will shift to the right (from cdf1 to cdf2) after removing the license fee, while the cumulative distribution of nonbuyers lies on the left to that of the buyers. That is to say, the buyers would buy more expensive cars (on average RMB 8,448 more), and some nonbuyers would buy cars, but less expensive cars than the current car buyers (on average RMB 21,668 cheaper). The gap in the distribution between cdf2 and cdf3 suggests that high-income consumers are more likely (or able) to purchase expensive cars since the only difference between buyers and nonbuyers is their income, while the gap in the distribution between cdf1 and cdf3 suggests that when consumers' budgets increase due to the license fee removal, they can afford the preferred high-end cars and so the price distribution shifts to the right.²⁰

Table 7 shows the comparative statics for our counterfactual analyses. Removing the license fee will lower the sale-weighted average price by 2.88% due to the entry of low-income con-

²⁰A substitution effect also exists given that the price enters the indirect utility function in log terms. However, $\log(y_{imt} - p_{jmt})$ shifts down by a similar scale for all the products, so the income effect dominates the substitution effect.

sumers: the mean annual income of car buyers decreases by 12.12%.

The above counterfactual analysis is based on the assumption that the choice set in Shanghai is exogenously fixed and will not change even if the license fee is removed, although in reality it is endogenously determined by demand. Some low-price models could be unobservable in our data because they are unavailable or actually available but not purchased since high-income consumers prefer high-quality/high-price vehicles. Removing the license fee may shift demand towards these low-price models since low-income consumers can afford them now. Ignoring the change in choice set will underestimate the effect of removing the license fee. To take into account the possible change in choice set, we enlarge the choice set in Shanghai by including the low-end cars only observable in Beijing for our second counterfactual analysis.

Indeed, the observed product set available in Shanghai in June 2010 is almost a subset of that in Beijing. There are 214 car models sold in both metropolises with an average price of RMB 156,511. The other 93 models with an average price of RMB 132,668 are only observed in Beijing. There are only two models uniquely observed in Shanghai, both of which are luxury cars with an average price of RMB 329,300. We simulate that the 93 models are available in Shanghai, and assume their unobserved product characteristics (ξ_{jmt}) are the same as in Beijing. Column (iii) in Table 7 shows that the average price further lowers by 1.51% ($(165.1 - 162.6)/165.1$).

Given that incomes between Shanghai and Beijing are similar and so the only difference between these two cities in our analysis lies in the license fee, our counterfactual analysis results seem suspicious. Predicted sales for Shanghai is less than half of the sales of Beijing, even after removing the license fee. Without solving this puzzle, the other predictions are also unbelievable.

We notice that the estimates of location-specific intrinsic value in Beijing is positively significant, which could lead to the predicted sales gap between these two cities. To test this, we conduct the third counterfactual analysis, assuming that the location-specific intrinsic value of Shanghai is equal to that of Beijing. Column (iv) of Table 7 shows that this will perfectly solve our puzzle: predicted sales are more than double the sales at scenario 2 and very close to

those for Beijing, with average price and income similar to those in the second scenario. These results also suggest that the license fee in Shanghai can control the vehicle population, but it may not be the main factor contributing to the much lower number of vehicles in Shanghai. The lower intrinsic value for a vehicle may play a more important role.

Table 8 presents the simulation results for scenario 4. When we apply the VQS to the Beijing auto market, car sales drop by 40.60% to 25,586 units, which is still more than double the sales in Shanghai, due to the much higher intrinsic preference for vehicles in Beijing. This reinforces our previous conclusions that the lower intrinsic preference for vehicles in Shanghai play a more important role in vehicle control.

7.2 Impact on the indigenous brands

The market demand shift toward high-end cars due to VQS may favor the joint ventures but discourage the indigenous manufacturers. Tables 7- 8 show that the market share of indigenous brands in both Shanghai and Beijing would be slightly higher after removing VQS, indicating that VQS impacts the market structure to some extent. The reason that the market share changes are only moderate is as follows: although the low-income nonbuyers enter the market and buy low-end products, which are usually indigenous brands, other buyers climb up the ladder of affordable budget after removing the VQS, and switch to foreign brands as shown by Figure 4. Eventually, VQS shrinks the market shares of indigenous brands only moderately.

However, the long-term impact of VQS is more profound. VQS cuts the sales of indigenous brands into half (column 2 and 3 in Table 7). In the short run, this makes it harder for indigenous brands to gain a competitive edge. Since the output of the indigenous brands is relatively small, they are not able to take advantage of the economies of scale that are crucial for lowering costs in the automobile industry. In the long run, such a drop in sales will slow down the learning-by-doing process. Li, Xiao and Liu (2013) find that learning by doing significantly decreases the marginal cost of the Chinese automobile manufacturers. In particular, the indigenous brands have fallen behind the joint ventures in technology. The drop in sales

will slow down the technology accumulation and put the indigenous brands at a further disadvantage in the long run. Hence, VQS contradicts the central government policy of supporting indigenous brands. Alternative policies that could effectively control the vehicle population and also benefit indigenous brands would be more in line with the government's goals.

7.3 Alternative Policy

Despite the effectiveness of VQS in controlling the vehicle population and reducing air pollution and traffic congestion, it has been subject to criticism. First, the license fee was almost equal to the average annual income in Shanghai during 2009 and 2010. Low-income consumers cannot afford the license fee on top of a car, so they consider the system unfair since it is likely to keep low-income people out of the car market. Second, the system could conflict with the central government policy as discussed before.

In this section, we examine another policy, that complies with the purpose of vehicle control, to see if this policy can answer these criticisms. This is the first registration tax system imposed by the Hong Kong government to encourage the use of environment-friendly petrol private cars with low emissions and high fuel efficiency. Unlike the Shanghai VQS, the registration fee varies by vehicle price under this tax system. (See Table 9). This tax system could resolve the fairness argument since its tax rate is progressive in vehicle prices.

We check its effectiveness by simulation. Applying this system to Beijing and Shanghai, we predict the market shares and present the results in Table 10. Our results show that such a tax system would be as effective as the VQS in that total sales in both Beijing and Shanghai are very similar to those under VQS. Comparing the average prices under these two systems, however, we observe that consumers tend to purchase lower-price vehicles under the tax system. Also, the consumers' average income is lower, meaning the low-income consumers are not crowded out. Moreover, the market shares of indigenous brands increase by over 60% in both cities, which complies with the interest of the central government. From the local perspective, such a tax system could bring in as much revenue as the VQS does. In conclusion, a tax system with progressive tax rate could be a good substitute for the current Shanghai VQS.

8 Conclusion

This paper investigates the impact of the unique vehicle quota system of Shanghai, China, on two passenger vehicle markets. The empirical findings suggest that conditional on purchase of the license, consumers intend to purchase high-end vehicles with high prices since the customers who can afford the license are less price-sensitive. Hence, this system puts the manufacturers producing low-end cars at a disadvantage.

The counterfactual analyses show that the vehicle quota system is effective in vehicle control. However, it pushes out low-income car buyers, who are more likely to buy indigenous brands. This contradicts the central government policy to support indigenous brands. A simulation of the vehicle registration tax system of Hong Kong shows that a progressive tax system is as effective as the quota system in vehicle control but also is able to protect the indigenous brands.

Appendix

This section introduces the definition of product segments. We divide the vehicles into five segments in the conventional way of the Chinese auto industry. In terms of features and functions, vehicles can be divided into three categories: sedan, Sport Utility Vehicle (SUV) and Multi-Purpose Vehicle (MPV). For each category, the manufacturers usually define segments based on the length of the vehicles as shown in Table 11. We aggregate the parallel segments of different categories, and name them as mini, small, intermediate, large and luxury vehicles. The statistics of some features for each segment are listed in Table 11. It shows that the mean prices and features are quite different across segments.

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Table 1: Comparison of Characteristics in Beijing and Shanghai in 2010

Variables	Beijing	Shanghai
Average annual income of urban residents (RMB)	29,073	31,838
Number of households in selected districts	6,664,336	6,295,784
Average number of people in a household	2.8	2.9
Average savings	90,808	76,933
Average savings over income	3.35	2.58
Area (square kilometers)	16,410.54	6,340.5
Length of operation urban metro lines (km)	336	452.57

Note: The above data are from Beijing / Shanghai Statistical Yearbook or census.

Table 2: Comparison of car prices sold in Beijing and Shanghai in 2010

Variables	mean	std	p10	p25	p50	p75	p90	Observations
Price in Beijing	141,370	92,833	55,600	81,900	109,800	179,900	236,800	642,810
Price in Shanghai	169,289	88,598	89,700	108,800	149,800	199,900	288,000	122,793

Note: we include cars used in the demand estimates.

Table 3: Summary Statistics

Variables	mean	std	p10	p25	p50	p75	p90	Observations
Model level								
Price (thousand RMB)	155.350	130.386	49.900	76.069	108.800	183.767	329.800	484
Height (m)	1.5438	0.1355	1.435	1.465	1.485	1.576	1.765	484
Width (m)	1.7544	0.0862	1.645	1.695	1.765	1.820	1.822	484
Length (m)	4.4592	0.4078	3.890	4.264	4.531	4.762	4.981	484
Fuel consumption (liter/100km)	8.226	1.641	6.5	7	8	9.29	10.5	484
Horsepower (kw)	98.545	35.743	63	76	90.40	118	147	484
Model-market-time level								
Sales per market (units)	128.6	200.9	9	17	48	153	358	10,534

Note: A geographic market is defined as a province / metropolis, while time is a month.

Table 4: Results for Demand Estimation (1)

	Logit	Nested logit	Nested logit	Random coefficient nested logit
Model	(i)	(ii)	(iii)	(iv)
IVs	No	No	Yes	Yes
Budget constraint	No	No	No	Yes
Explanatory variable				
Segments (σ)		0.6423*** (0.0052)	0.6047*** (0.0082)	0.6032*** (0.0081)
Total price (RMB in 2010)	-0.0013*** (0.0002)	-0.0040*** (0.0001)	-0.0112*** (0.0003)	- -
ln(savings - total price)				2.4606*** (0.1840)
Width (m)	1.7288*** (0.2842)	3.0198*** (0.1811)	2.2030*** (0.2110)	3.1762*** (0.2420)
Length (m)	0.9761*** (0.0543)	1.0282*** (0.0346)	0.9258*** (0.0402)	1.0090*** (0.0423)
Fuel consumption (liter/100km)	-0.2153*** (0.0126)	-0.2511*** (0.0080)	-0.1160*** (0.0099)	-0.1628*** (0.0120)
Horsepower (kw)	-0.0046*** (0.0008)	0.0034*** (0.0005)	0.0228*** (0.0008)	0.0202*** (0.0009)

Note: The five segments are mini, compact, intermediate, standard, and luxury.

Total price is defined as the sum of price and average license fee.

Dummy for 2009, dummy for Korean cars, and dummy for Beijing are both omitted.

Numbers in parentheses are standard deviations.

Asterisks indicate significance at 10% (*), 5% (**) and 1% (***).

Month dummy variables are also included.

Table 4: Results for Demand Estimation (2)

	Logit	Nested logit	Nested logit	Random coefficient nested logit
Model	(i)	(ii)	(iii)	(iv)
IVs	No	No	Yes	Yes
Budget constraint	No	No	No	Yes
Explanatory variable				
Dummy for a Shanghai brand sold in Shanghai	0.8537*** (0.0467)	0.5644*** (0.0298)	0.3279*** (0.0356)	0.3973*** (0.0319)
Dummy for a Beijing brand sold in Beijing	0.1204** (0.0550)	-0.0285 (0.0350)	0.0990** (0.0407)	0.1260*** (0.0407)
Dummy for the year of 2010	0.0861*** (0.0229)	0.1689*** (0.0146)	0.1464*** (0.0170)	0.2174*** (0.0166)
Dummy for American cars	-0.0305 (0.0606)	-0.2172*** (0.0386)	-0.0455 (0.0450)	0.0052 (0.0357)
Dummy for European cars	0.2303*** (0.0575)	0.1736*** (0.0366)	0.7407*** (0.0452)	0.7834*** (0.0384)
Dummy for Japanese cars	0.3529*** (0.0565)	0.0462 (0.0360)	0.1900*** (0.0419)	0.2404*** (0.0340)
Dummy for domestic cars	-0.7112*** (0.0547)	-0.7173*** (0.0348)	-0.7751*** (0.0404)	-0.8216*** (0.0341)
Dummy for Beijing	1.1015*** (0.0283)	1.3047*** (0.0181)	0.9752*** (0.0225)	0.7458*** (0.0276)
Observations	10,534	10,534	10,534	10,534
R ²	0.2629	0.7016	0.5971	-

Note: The five segments are mini, compact, intermediate, standard, and luxury.

Total price is defined as the sum of price and average license fee.

Dummy for 2009, dummy for Korean cars, and dummy for Beijing are both omitted.

Numbers in parentheses are standard deviations.

Asterisks indicate significance at 10% (*), 5% (**), and 1% (***).

Month dummy variables are also included.

Table 5: Summary of Price Elasticities (Model (iv))

Own-price elasticities	
Mean	-4.3583
25% quartile	-4.6785
Median	-4.1192
75% quartile	-3.1705
Cross-price elasticities	
Mean	0.0102
25% quartile	0.0000
Median	0.0000
75% quartile	0.0032

Table 6: Differences of Car Models Sold in Beijing and Shanghai in June 2010

	Common	Only in Beijing	Only in Shanghai
Number of models	214	93	2
Average price (RMB in 2010)	156,511	132,668	329,300
Ratio of models of indigenous brands	0.2336	0.6237	0
Ratio of models manufactured in Shanghai	0.2477	0.0323	0
Ratio of models manufactured in Beijing	0.0748	0.0968	0

Table 7: Counterfactual Analysis of Car Sales in Shanghai in June 2010

	Previously	Removing license fee	Adding models sold only in Beijing & removing license fee	Adding models sold only in Beijing & making outside option the same as Beijing
Sales of cars sold	11,381	19,778	20,220	42,216
Sales of cars of indigenous brand	1,151	2,107	2,584	5,421
Inside market shares of indigenous brands	0.1011	0.1065	0.1278	0.1284
Sales weighted price of cars sold (RMB in 2010)	170,014	165,094	162,646	162,181
Mean of income of car buyers (RMB in 2010)	64,500	56,681	56,273	56,042

Table 8: Counterfactual Analysis of Car Sales in Beijing in June 2010

	Previously	Adding license fee of Shanghai
Sales of cars sold	43,076	25,586
Sales of cars of indigenous brand	8,397	4,974
Inside market shares of indigenous brands	0.1949	0.1944
Sales weighted price of cars sold (RMB in 2010)	145,501	148,281
Mean of income of car buyers (RMB in 2010)	44,168	49,690

Table 9: First Registration Tax Rate in Hong Kong

Class of motor vehicle	Tax rate
a. the first HKD150,000	40%
b. on the next HKD150,000	75%
c. on the next HKD200,000	100%
d. on the remainder	115%

Note: 100 HKD was about 88 RMB on January 1, 2010.

1 USD was about 6.82 RMB on January 1, 2010.

Table 10: Counterfactual Analysis of Adding Tax Rate as Hong Kong in June 2010

	Adding license fee of Shanghai to Beijing	Adding tax rate as Hong Kong to Beijing	Previously in Shanghai	Adding tax rate as Hong Kong to Shanghai
Sales of cars sold	25,586	23,097	11,381	9,028
Sales of cars of indigenous brand	4,974	7,370	1,151	1,596
Inside market shares of indigenous brands	0.1944	0.3191	0.1011	0.1768
Sales weighted price of cars sold (RMB in 2010)	148,281	106,511	170,014	127,836
Mean of income of car buyers (RMB in 2010)	49,690	44,970	64,500	59,620
Revenue of license fee / tax (million RMB in 2010)	1033.1	1056.8	459.5	503.9

Table 11: Vehicle segments and statistics

		Segments based on vehicle length (m)			Segment Mean		
	Sedan	SUV	MPV	No. of observations	Price (RMB yuan)	Displacement (liter)	Weight (kg)
Mini	<4.00	<4.00		37	45335.65	1.16	969.24
Small	4.00-4.20	4.00-4.30	<4.10	149	93942.94	1.62	1238.53
Intermediate	4.20-4.45	4.30-4.60	4.10-4.20	206	140166.40	1.88	1393.37
Large	4.45-4.80	4.60-5.00	4.20-4.60	26	153662.00	2.30	1817.46
Luxury	>4.80	>5.00	>4.6	66	417085.60	2.63	1751.92

Figure 1: The Price and Quota of Private Car Licenses in Shanghai

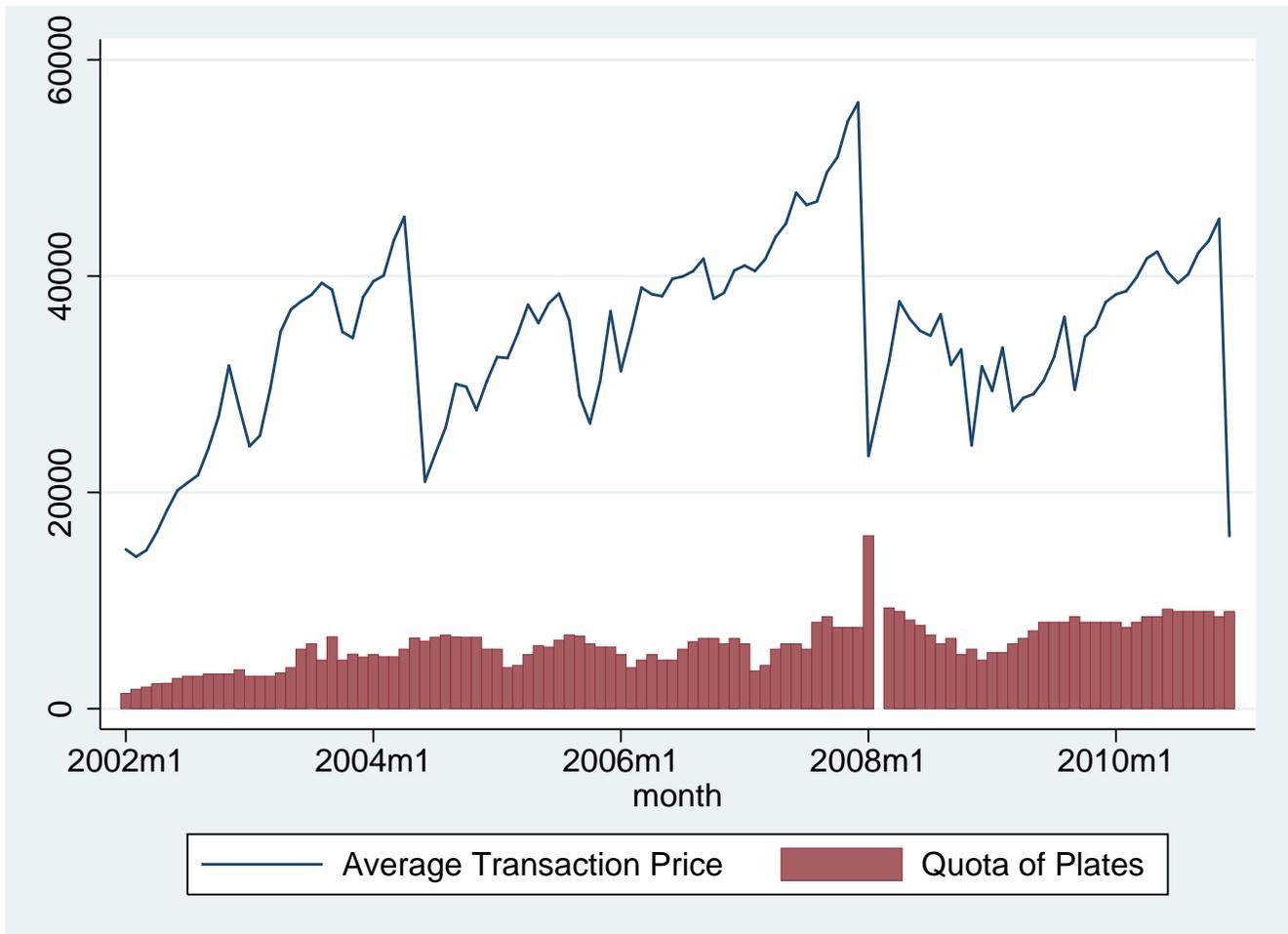


Figure 2: The Cumulative Distribution Functions of Price of Cars Sold in Beijing and Shanghai in 2010

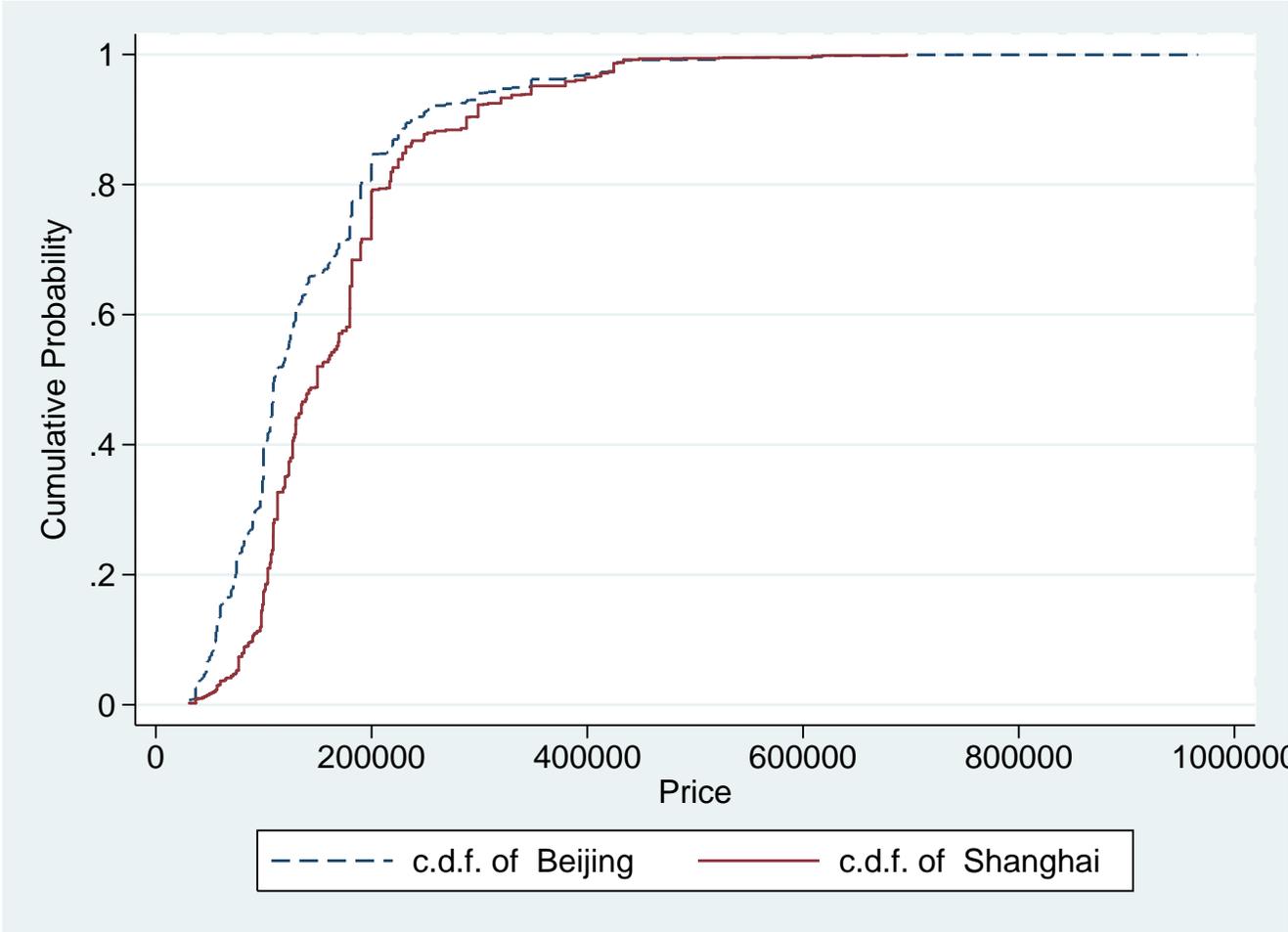


Figure 3: Quality Choice of Consumers with Different Incomes

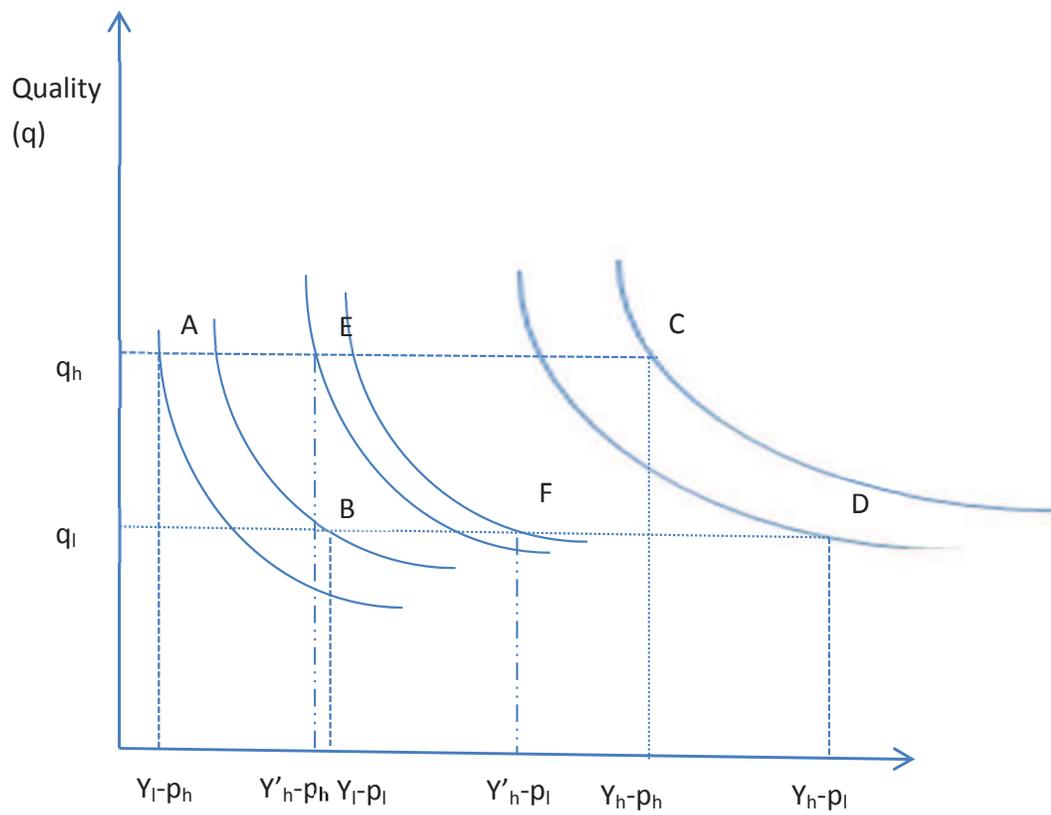
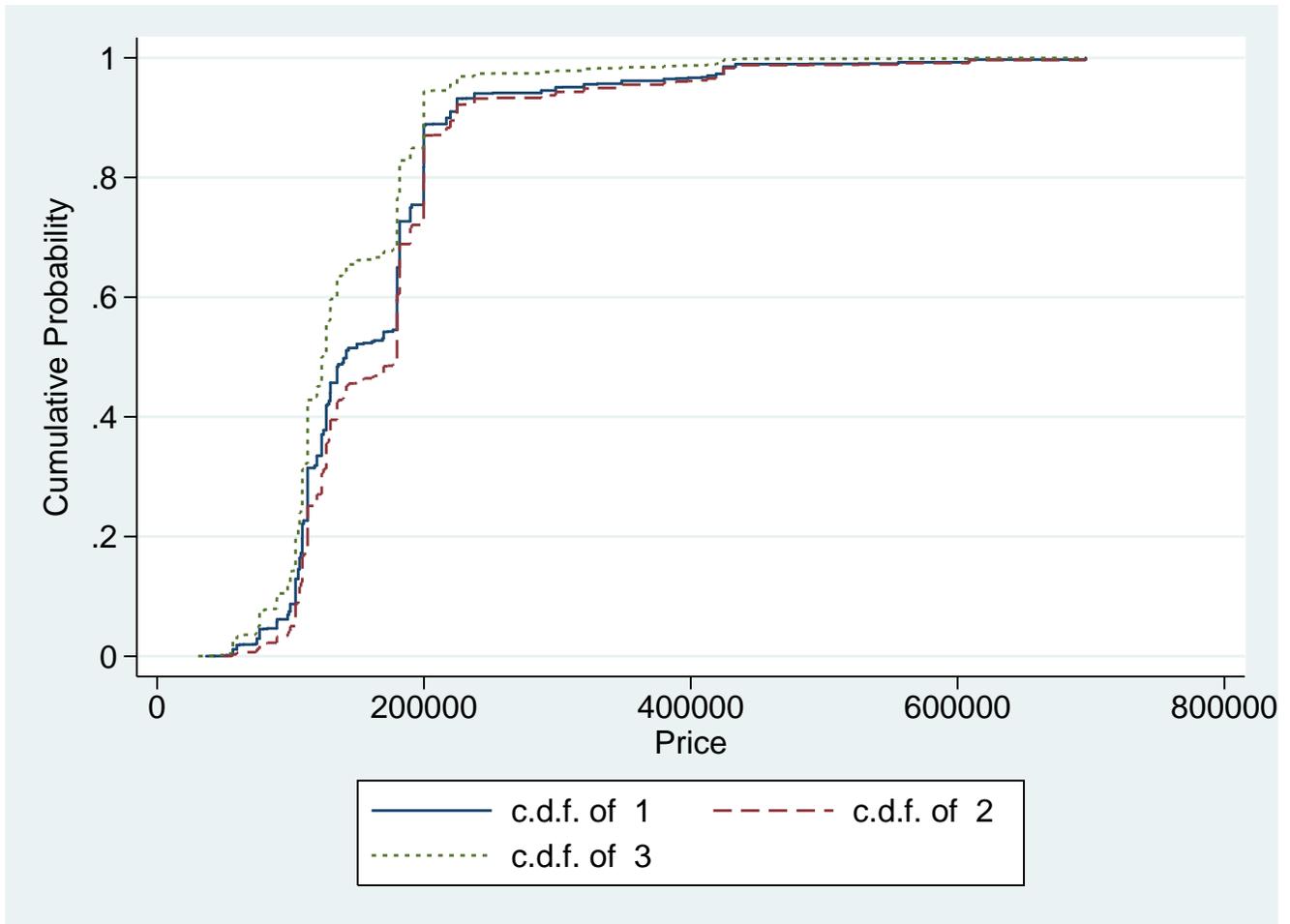


Figure 4: The Simulated Cumulative Distribution Functions of Car Prices without License Fee



Note: 1 stands for price distribution of cars bought by current buyers in Shanghai (benchmark);
2 stands for price distribution of cars bought by current buyers in Shanghai if there is no license fee;
3 stands for price distribution of cars for people who have not bought a car but would buy a car if there were no license fee in Shanghai.