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ABSTRACT

The efficiency of resource allocation is often analyzed in static frameworks with a focus on the cross-sectional heterogeneity in the willingness to pay among users. When the resource is durable in nature, the temporal heterogeneity could be important in assessing the efficiency properties of different allocation mechanisms. This paper uses a dynamic model to empirically quantify the efficiency outcome of using lotteries to allocate scarce resources among forward-looking consumers. In the context of the lottery policy for vehicle licenses in Beijing, our analysis shows that lotteries significantly affect intertemporal decisions in that households participate in lotteries at least four years earlier on average than they would be in a counterfactual environment of no quantity constraint. The welfare loss due to temporal heterogeneity and resulting changes in participation decisions accounts for over half of the total welfare loss from the lottery policy. The analysis highlights the importance of taking dynamic efficiency into account in designing resource allocation mechanisms.

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1 Introduction

Government agencies and institutions often use lotteries to allocate scarce resources. Examples include, but are not limited to, subsidized housing, hunting permits, charter school and community college admissions, and medical interventions such as vaccines and organs for transplants. The right to use the resources obtained through lotteries in these settings is generally non-transferable. As a result, lotteries could lead to welfare loss because the resources may not be allocated to the users who value them the most. The literature has largely focused on the inefficiency of using lotteries for resource allocation arising from the cross-sectional heterogeneity in the willingness to pay (WTP) across users in a static framework (Borenstein and Zimmerman, 1988; Glaeser and Luttmer, 2003; Hazlett and Muñoz, 2009; Davis and Kilian, 2011; Li, 2017).

This paper investigates intertemporal decisions as an additional and potentially more important source of inefficiency from lotteries. Due to the quantity constraint, a lottery system delays access to the resource in question, and the delay could be substantial when the quantity constraint (or cap) is tight relative to the underlying demand. In anticipation of the delay, agents who need the resource only in the future may enter the lottery pool before they need the resource. The participation of these agents in the market without an immediate need of the resource reduces the probability of winning for all agents in the lottery pool. The incentive to preemptively enter the lottery pool is stronger when the (expected) odds of winning are lower, further exacerbating the waiting period for those who have an immediate need for the resource. Misallocation of this kind is temporal in nature. We define the welfare loss from this channel as dynamic inefficiency in resource allocation.

Dynamic inefficiency could arise in many institutional settings in which a random allocation mechanism is used to allocated scarce resources. The US government uses a lottery policy to allocate H-1B working visa among foreign nationals. Kato and Sparber (2013) argue that the reduction of H-1B visa quota in 2003 led to a decline in the quality of job applicants because it discouraged high-ability international students from pursuing education in the US. Rent control provides another prominent example. Several US cities address housing affordability among low-income households with lotteries that allocate the limited number of rent-regulated apartments to those in need. Misallocation arises when the available units go to those with relatively low willingness to pay (Glaeser, 1996). Because housing decisions are inherently dynamic, the rent control policy has the potential to create dynamic inefficiency by affecting household temporal decisions (Basu and Emerson, 2000; Diamond et al., 2019). Recent expansion of the rent control regulation has reignited the debate over the efficiency of this type of policy.[1] However, there is a lack of empirical analysis on the importance of dynamic inefficiency in these settings.

[1]California and New York State passed rent laws to expand the rent regulation to the entire states in the face of rising housing costs. See https://www.nytimes.com/2019/06/12/nyregion/rent-regulation-laws-new-york.html, and https://www.nytimes.com/2019/09/11/business/economy/california-rent-control.html.

Using a model of dynamic demand, we quantify the extent of dynamic inefficiency in the context of a vehicle license lottery policy in Beijing. In 2011, the Beijing municipal government introduced a vehicle quota system to curb the dramatic increase in vehicle ownership and to combat worsening traffic congestion and air pollution. The policy puts a cap on newly issued vehicle licenses and uses a non-transferable lottery system to allocate the limited number of licenses. A salient feature of the lottery system is the rapidly expanding lottery pool, and, in turn, dramatically shrinking winning odds. In January of 2011, around 180,000 households applied to participate in the lottery. This number increased to 1.34 million by the end of 2012, and, to over 12 million by the end of 2017. The enormous expansion of the lottery pool resulted in a significant plunge of the winning odds: from 9.4 percent in January 2011 to about 1 percent by the end of 2012, and, further, to 0.1 percent by the end of 2017 as shown in Figure 1.

In contrast to the rapid growth of the number of lottery participation, vehicle sales increased at a much slower pace in the periods before the policy and in cities that have not implemented a vehicle quota system. Sales in Beijing were about 0.8 million in 2010, the year before the lottery policy, and grew steadily at a rate of about 2 percent in each month. Vehicle sales in Tianjin, a neighboring city of Beijing, showed a slight decrease from 2010 to 2011, and moderate growth from 2011 to 2012 as shown in Figure 2.[2] This contrast suggests that the policy may have induced households to enter the lottery pool far earlier than when they would have bought a vehicle in the absence of such a policy. The induced change in timing decisions could have significant welfare implications.

To quantify the welfare impact, in particular, the potential dynamic inefficiency from the lotteries, we develop and estimate a structural model of dynamic demand for both license plates and vehicles. A dynamic model is necessary to capture consumer forward-looking behavior and intertemporal substitution for the following two reasons. First, in contrast to the US market, the vehicle market in China has been experiencing rapid product turnover and price changes as an emerging market (Li et al., 2015). In addition, while vehicles are durable, household characteristics, such as income, change over time. As a result, the purchase timing is an important choice margin for agents. A dynamic demand model better suits such a context (Gowrisankaran and Rysman, 2012). Second, vehicle licenses are also durable goods. Under the lottery policy, households need to decide when to enter the lottery pool based on both their anticipated future needs and the winning odder. A dynamic model is capable of better capturing these decisions on when to participate in the process.

Our model builds on the empirical methodology of Gowrisankaran and Rysman (2012) (henceforth GR), who develop a dynamic framework nested with a BLP-style demand to capture product differentiation, endogeneity of prices, persistent consumer heterogeneity, and repeat purchases over time. In contrast to the GR framework, our model assumes households make decisions in two

[2] In 2-14, Tianjin started to implement a quota policy involving a hybrid system of auction and lottery.

stages. Households first decide whether to enter the lottery, and then, conditional on winning, they decide when to make a purchase and which vehicle model to choose. The utility received from lottery participation in the first stage is the expected value of purchasing a vehicle conditional on winning. The heterogeneous preference toward owning a vehicle in the second stage affects the utility of lottery participation. Households that are likely to receive a higher utility from buying a vehicle are more likely to participate in the lottery. In addition, the model allows household income and the need to have a vehicle (due to both observed and idiosyncratic reasons) to change over time, leading to temporal heterogeneity among households.

To address time-varying demand shocks that could confound the lottery policy, we leverage the common trend assumption implicitly employed in the difference-in-differences (DID) framework as in Li (2017) and use that to construct additional moment conditions in estimation. Specifically, we use Tianjin, a neighboring city with a large population, as the control group. Both Tianjin and Beijing are among the four directly administered municipalities in China. However, Tianjin did not have a vehicle quota system during the sample period. Through both graphical and regression analysis, we show that the vehicle markets in the two cities exhibited similar trends before the policy. The advantages of using the common-trend assumption to aid identification of the structural model are twofold: First, the common-trend assumption does not rely on the maintained exogeneity assumption that unobserved product attributes are uncorrelated with observed product attributes; Second, it helps regulate the unobservable demand shocks in Beijing after the policy, which turns out to be crucial in estimating the counterfactual vehicle sales.

Our analysis shows that the lottery policy alters the intertemporal decisions of vehicle purchase. Households enter the lottery pool at least four years earlier on average than they would have purchased a vehicle in the absence of a lottery policy. Moreover, lottery-winning households purchase vehicles six months earlier on average than they would have if the lottery policy were not in placed.[3] These timing decisions, especially the entrance of non-urgent buyers into the lottery pool, give rises to the dynamic inefficiency. The total welfare loss from the lottery policy relative to the first-best allocation has two components. The first component is due to static misallocation characterized by the difference between the first best and the counterfactual scenario where licenses are randomly allocated with equal probability among households that would purchase a vehicle in each period in the absence of the quantity constraint. This counterfactual scenario does not allow households to adjust their timing decisions and therefor exclude dynamic considerations. The second component is dynamic inefficiency characterized by the difference between the above counterfactual scenario and the lottery policy. This component is driven by the changes in time decisions induced by the lottery policy. Our analysis shows that the welfare loss from dynamic inefficiency amounted to 58

[3]The policy requires lottery winners to purchase a vehicle within six months. Those who fail to comply with this rule are not allowed to re-enter the lottery within three years.

Billion RMB, accounting for 52 percent of total welfare loss from the lottery policy during 2011 and 2012.[4]

This study contributes to the literature in the following three dimensions. First, it adds to the literature to understand the efficiency consequences of various mechanisms for resource allocation. Researchers have argued that lotteries represent a fair mechanism for allocating resources, especially when objects are indivisible (Aubert, 1959; Eckhoff, 1989; Fienberg, 1971; Hofstee, 1990).[5] In addition, Boyce (1994) argues that lotteries can prevent the rent-seeking behavior and speculation, and therefore, can preserve more economic rents for all participants than they would have received under alternative allocation mechanisms such as auctions, queues or merits-based decision making procedures.[6] Several empirical papers examine the welfare loss from resource misallocation through lotteries. Glaeser and Luttmer (2003) and Davis and Kilian (2011) documented significant misallocation under lotteries through price controls in the housing market in New York City and the US residential market for natural gas, respectively. Closely related to our study is Li (2017), who quantifies and compares the welfare consequences of lotteries and auctions in a static framework by taking into account both allocative efficiency and automobile externalities post-allocation. In the same context of vehicle license allocations, Xiao et al. (2017) analyzes the welfare effect of the auction mechanism in Shanghai while Huang and Wen (2019) focuses on the auction-lottery hybrid mechanisms used in other four Chinese cities. These empirical studies have all focused on the cross-sectional heterogeneity among users, and the resulting static misallocation. By contrast, our paper identifies an additional source of misallocation from inter-temporal considerations, and shows that dynamic inefficiencies could be much larger.

Second, our paper fits into the growing literature that uses dynamic models to empirically examine the welfare impacts of resources allocation and environmental regulations. Examples include (but not limited to) the study of water resource allocation (Timmins, 2002; Donna and Espín-Sánchez, 2016), the common-pool problem in fisheries (Huang and Smith, 2014), and regulation of air pollution and greenhouse gas emissions regulations in the cement industry (Ryan, 2012; Fowlie et al., 2015). Our study adapts an empirically tractable structural model of demand estimation used in Schiraldi (2011), Gowrisankaran and Rysman (2012) and Lee (2013) to analyze the misallocation and dynamic efficiency properties of lotteries.

Third, this study adds to the literature on the automobile market in China as well as on regulations to address negative externalities (e.g., traffic congestion and air pollution) from automobile

[4]The exchange rate was about 6.5 USD/CNY between 2011 and 2012.

[5]Kahneman et al. (1986) uses the survey experiment to show that consumer sometimes value "fairness" as a more important consideration in certain situations. For example, in their research context, which addresses the allocation of convert tickets, agents prefer queues to lotteries or auctions.

[6]Hazlett and Michaels (1993) empirically estimate rent-seeking costs in cellular telephone license lotteries conducted by the US Federal Communications Commission that required participants to pay an entry fee to a consulting firm to submit an application.

usage. To our knowledge, this paper provides the first analysis to apply a dynamic framework to study automobile demand in China. The rapid growth of China's automobile industry offers a fertile ground for exploring interesting questions about market power (Deng and Ma, 2010), pricing decisions and collusion (Hu et al., 2014) , price evolution over time (Li et al., 2015), local protectionism in the automobile market (Barwick et al., 2017), and quality upgrading (Bai et al., 2019). The rapid increase in vehicle ownership in China over last two decades has significantly contributed to two pressing urban challenges in China: air pollution and traffic congestion. To combat these challenges, central and local governments have adopted a series of policies aimed at reducing vehicle ownership and usage. Currently seven cities in China employ a vehicle quota system with different allocation mechanisms such as lotteries, auctions, or a combination of the two as shown in Appendix Table 1. In light of the limited understanding of the effectiveness and efficiency of these policies, this study presents the first analysis on the dynamic inefficiency of the lottery policy.

The rest of the paper is organized as follows: Section 2 presents a stylized theoretical model to illustrate how dynamic inefficiency arises in resource allocation. Section 3 describes the background of the vehicle lottery policy in Beijing and introduce the data pattern and reduced-form evidence. Section 4 presents a structural model of lottery participation and demand for vehicles. It also outlines the identification and the estimation strategies. Section 5 presents the estimation results. Section 6 presents counterfactual simulations and welfare analyses. Section 7 concludes.

2 Dynamic Inefficiency - A Theoretical Illustration

In this section we illustrate the dynamic inefficiency in resource allocation through a stylized theoretical model. The model considers a market with consumers of unit measure. Consumers are separated by two types according to the utility received from the resource, u_h for the high type h and u_l for the low type l. For both types, the utility received from the outside option is normalized to zero. We assume that the utility received by the low type is not only lower than the utility received by the high type, but also lower than the utility received from the outside option. That is, the low type should not receive the resource under an efficient allocation mechanism. Formally, the assumption is:

Assumption 1. $u_h > 0 > u_l$.

Suppose that the resource is allocated via lottery, and that the total amount of resource to be allocated in each period is capped at q. Each agent faces a two-period decision problem with her type changing over time. At the beginning of each period, the agent can privately observe the realization of her own type, and then she decides whether or not to participate in the lottery. We denote r_t as the probability that an agent becomes the high type at period t and the probability of this is a common knowledge to all consumers in the market. To avoid trivial results, we impose the following assumption to ensure that the total resources to be allocated are always less than the total number of high-type consumers in the first period,

Assumption 2. $q < r_1 < 1, \forall t$.

We focus on the symmetric equilibrium where consumers of the same type adopt the same (mixed) strategy of participating in the lottery at each period. An agent's strategy is a probability function σ_t^x that maps the agent's type x and the agent's expectation on the probability of winning. Denote π_t^e as the expected probability of winning of period t, and π_t as the realized probability of winning. The equilibrium is defined as the following:

Definition 1 (Market Equilibrium). A market equilibrium is a tuple $(\sigma_t^x, \pi_s^e, \pi_t)$,where $t, s \in \{1,2\}$ and $x \in \{l,h\}$ such that
(Optimality) For every t, σ_t^x is the best response for consumer of type x given $\pi_s^e, s \in \{1,2\}$, and
(Rational expectation) For $s \in \{1,2\}$, $\pi_s^e = \pi_s$.

To ease exposition, we assume that all consumers become the high type in the second period, i.e., $r_2 = 1$. In this case, an agent's payoff from participating in the second period is always positive. Therefore all consumers will choose to participate in that period. An agent of type $x \in \{h,l\}$ who enters the lottery in the first period will receive a utility from the resource if winning, or an expected payoff in the next period if not. The total discounted payoff of the agent at period $t = 1$, denoted as V_1^x, is:

$$V_1^x = \pi_1^e(u_x + \beta u_h) + (1 - \pi_1^e)\beta \pi_2^e u_h. \tag{1}$$

If the consumer does not enter the lottery in the first period, the payoff (denoted as W_1^x) is:

$$W_1^x = \beta \pi_2^e u_h. \tag{2}$$

As u_h is positive, entering in the lottery in the first period is a weakly dominating strategy for the high type, and strictly dominating when the expected probability of winning π_1^e is strictly positive. The probability of winning in the first period is at least q - the winning odds when all consumers participate in the lottery. By the rational expectation condition, the high type will always choose to enter the lottery in the first period.

For the consumers of low type, they face the following trade-off in the first period. On the one hand, those who enter the lottery in the first period may suffer a loss when winning because they will receive a negative utility from the resource. On the other hand, by entering the lottery, they can increase the chance of getting the resource in the second period when they become high type, and receive a positive utility from the resource. The low type consumers will choose to enter the lottery in the first period if the latter effect dominates. However, lotteries become less efficient when the low type consumers enter in the first period, because that will reduce the probability of winning for the high type consumers, and the resource may be misallocated to these low type consumers. The following proposition shows that under certain conditions, the low type consumers participate in the lottery during the first period with a positive probability in equilibrium.

Proposition 1. *Under assumptions 1-2 and $u_h \geq -\frac{1-q}{(1-2q)\beta} u_l$, there exits an unique equilibrium where the low type consumers participate the lottery in the first period with a positive probability.*

Proof. Because all the high types enter the lottery in the first period, the total number of participants in the first period is greater than the amount of resources to be allocated by assumption 2. The total number of consumers who do not receive the resource at the beginning of the second period is $1-q$. Given that all consumers become the high type and that they will enter the lottery in the second period, the winning probability for the second period is $\frac{q}{1-q}$.

For the low type, the payoff difference between the two choices in the first period is

$$V_1^l - W_1^l = \pi_1^e (u_l + \beta(1-\pi_2^e) u_h).$$

Because the low types will enter the lottery in the first period as long as

$$V_1^l - W_1^l \geq 0$$

by rational expectation condition, $\pi_1^e > 0$ and $\pi_2^e = \frac{q}{1-q}$, we derive the required condition for u_h and u_l that ensures above equation to hold:

$$u_h \geq -\frac{1-q}{(1-2q)\beta} u_l. \tag{3}$$

□

The condition of equation 3 is easier to hold when the number of resources to be allocated q is smaller: when the low type agents expect a lower probability of winning, they will be more likely to enter the lottery in the first period because they are less likely to be penalized by entering (i.e., winning the resource when the utility received from the resource is negative).

The lottery policy results in efficiency loss for two reasons: First, some high type consumers face delays in receiving the resources due to the quantity constraint. Second, the resource might be misallocated to the low types in the first period. This second channel emerges due to the change in participation timing of the the low types. We define the welfare loss from this channel as dynamic inefficiency. We formalize the definition of dynamic inefficiency as follows:

Definition 2 (**Dynamic Inefficiency**)**.** The dynamic inefficiency is the difference between the welfare from allocating the resource to the high-type consumers only and that from allocating the resource to all lottery participants.

The dynamic inefficiency in the second period is zero because all consumers become the high type in that period. Thus, we focus the discussion on the first period. Under the condition in equation 3, all consumers will participate in the lottery in the first period, leading to the winning probability of q. Thus, the ex-ante welfare received in the first period is:

$$CS_{\text{Dynamic Misallocation}} = r_1 q(u_h + \beta u_h) + (1 - r_1) q(u_l + \beta u_h).$$

In the efficient equilibrium where the resource is allocated to the high types only, the ex-ante welfare is:

$$CS_{\text{Efficient Allocation}} = q(u_h + \beta u_h).$$

The welfare loss from dynamic inefficiency is $q(1 - r_1)(u_h - u_l)$. While the theoretical model assumes two types of consumers to ease exposition, our empirical analysis allows for much richer consumer heterogeneity in WTP for the resource.

3 Policy Background and Data

In this section, we first describe the vehicle lottery policy in Beijing. We then present the data and stylized facts.

3.1 Policy Background

As many large urban centers in fast-growing economies, Beijing has been facing severe traffic congestion and air pollution, routinely ranked as one of most polluted and congested cities in the world. According to Beijing Transportation Annual reports, average speeds during peak period declined from 36.4 km/h to 23.1 km/h in the morning (7:00-9:00) and from 32.3 km/h averaged 23.1 km/h to 20.9 km/h in the afternoon (17:00-19:00) during From 2005 to 2011. The average daily concentration of $PM_{2.5}$ was 78.8 ug/m^3 and 96.1 ug/m^3 in 2009 and 2010, compared to the WHO recommended level of 10 ug/m^3.[7] The hourly $PM_{2.5}$ frequently reached over 250 ug/m^3, a hazardous level considered by the US EPA.

Traffic congestion and air pollutions are direct consequences of the dramatic increase in vehicle ownership and usage in Beijing.[8] Along with the rapid growth in household income, annual sales of

[7] In China, public access to daily pollution measures was almost absent prior to 2013 (Barwick et al., 2019).

[8] According to Beijing Environmental Protection Bureau, exhaust emission from motor vehicles is the largest source of

new passenger vehicles in Beijing increased from 2.6 million units in 2005 to 4.8 million in 2010.[9] To combat traffic congestion and air pollution, on December 23rd, 2010, the Beijing municipal government unexpectedly announced the vehicle lottery policy that caps the monthly registration of new vehicles. The policy started in January 2011. Licenses are allocated through a publicly held lottery administered by the Beijing Municipal Commission of Transport. The lottery was originally held on 26th of each month, with approximately 20,000 licenses allocated to selected applicants from the lottery pool. Since then, modifications have been made, including reducing the cap, and changing the lottery from monthly to bimonthly.

Licenses from winning lotteries are not transferable, effectively preventing the reallocation of the resource in the market.[10] Lottery policy is also accompanied with a strict traffic control regulation. Out-of-state vehicles are not permitted to drive into the fifth ring road (within which the vast majority of business and population are located) during the weekday rush hours of 7:00 a.m. to 9:00 a.m., and 5:00 p.m. to 8:00 p.m. In addition, out-of-state vehicles need a special permit, valid for seven days only, to drive in Beijing.

Lottery participation has no monetary costs but does entail opportunity costs. To be an eligible applicant, the applicant must be a legal driver (with a valid driver's license) and be a resident of Beijing or a non-resident who has been paying income tax for at least five years in Beijing. Eligible applicants must sign into a government website, and fill out the application form online. A screening process then verifies the applicants' qualifications. People who have met these requirement and completed these steps are then allowed to submit an application to entering the lottery pool.

Salient features of the lottery policy in Beijing are the growing and excessive participation, and the increasingly low winning odds. These features are common among all cities that have implemented vehicle license lotteries.[11] Appendix Table 1 summarizes allocation mechanisms and winning odds across seven cities. In all cities that have incorporated lotteries into their allocation policy mechanisms, the winning odds had fallen below one percent by the end of 2017.

$PM_{2.5}$, accounting for 22 percent in the entire city and about one third in the urban core. Data from 2012 show that the second largest source of $PM_{2.5}$ is coal burning (17 percent) followed by dust from construction site (16 percent).

[9] The household vehicle ownership rate is 0.58 in Beijing, comparing to 0.46 in New York city and 1.16 in the U.S. from 2010 U.S. Census.

[10] A license is allowed to transfer to a new vehicle from a scrapped old one if legal owners of both vehicles are same. Anecdotal evidence suggests that vehicle lottery winners may rent their licenses to others through a black market, the practice is unlikely to be widespread. The legal owner (the winner of the lottery) is liable for paying the annual registration fee, traffic fines and emission inspections. Moreover, the owner is also liable for any damages and injuries that occur as the result of accidents.

[11] By the end of 2017, seven major cities in China had started vehicle quota system with two cities (Beijing and Guiyang) using lotteries to allocate vehicle licenses. Shanghai uses auctions. Tianjin, Guangzhou, Hangzhou, and Shenzhen have adopted a hybrid system that uses both lotteries and auctions.

3.2 Data

Our empirical analysis focuses on the lottery policy in Beijing and we include a nearby city, Tianjin in the analysis to aid identification. Tianjin is about 150km from Beijing. Beijing is the second largest city in China by population and Tianjin is the sixth largest.[12] In terms of average household income, Beijing experienced a slightly smaller increase in average income (42%) than Tianjin (49%) over the five-year study period. The inflation was 13.7% during the period. Characteristics of both cities are shown in Appendix Table 1.

We rely on four main data sets together with a variety of axillary data for our analysis. These data sets include information on 1) monthly new vehicle sales, 2) vehicle characteristics, 3) household survey data on vehicle ownership, and 4) household income distributions in Beijing and Tianjin.

The new vehicle sales data contain monthly sales by model (vintage-nameplate) in each city from 2008 to 2012. There are 21,228 observations with 1,769 distinct models.[13] Figure 2 plots monthly sales (in log) in each city. An important feature from the plot is that sales in the two cities track each other closely before 2011. The sales increase in December 2011 appeared to be stronger in Beijing than in Tianjin. This is likely due to the anticipation effect of the lottery policy announcement on December 23, 2010, just nine days before taking effect on January 1, 2011. The announcement led many households to rushed to buy a car within that last week of December. To examine whether the announcement effect may distort our results, we conduct robustness checks without the observations of last two months in 2010 and first month in 2011.

The data on vehicle characteristics data contain information on manufacturer suggested list price (MSRP), vehicle size, engine displacement, and vehicle segment.[14] Table 1 reports the summary statistics at the model-year-month level and segment-year-month level. The price is about RMB 300,000 for each model. The average price is higher than average annual household income in both cities suggesting that taking into account future income levels represents an important aspects of the process of deciding to buy a car. Vehicle prices are computed based on MSRPs and the sales tax in our analysis. The standard 10% sales tax was reduced to 5% in 2009, and 7.5% in 2010 for vehicles with engine displacement of no more than 1.6 liters. We utilize both the variation in the sales tax rates across time, and the engine displacement sizes in identifying the price coefficient.

MSRPs are set by manufacturers and are generally constant across locations and within a model

[12]Beijing and Tianjin are two of China's four directly administered cities. In the governance hierarchy, this designation places these cities at the same level of administrative subdivision as provinces, and right below the central government.

[13]The data source is R.L. Polk & Company (since acquired by IHS Markit), which provides market consulting services for a variety of industries including the automobile industry across the globe.

[14]Engine displacement is the total volume of all the cylinders in an engine. It is positively correlated with engine power output. Vehicle segment is the classification of vehicle models according to their prices, sizes, weight and displacements. For sedans, the segments are mini, small, medium, upper medium, large, and luxury .

year. The actual transaction prices may also include dealers' promotions, which are not observable to researchers. Using MSRPs as price may under estimate the competition level among retailers. At the same time, the use of a minimum retail price maintenance (RPM), which prevents retailers from selling at a price below a set minimum, was common in China during the study period. Our analysis uses MSRPs with the implicit assumption that the allocation mechanisms in Beijing do not affect firms' nor dealers' pricing strategies. The widespread use of minimum RPM prices means that, our results are not likely to be driven by the difference between MSRPs and actual retail prices.

To better understand the dynamic feature of the market, we present selected vehicle characteristics in Appendix Figure 1. The plot displays three important features. First, over the years show, average price declined-from more than 340,000 in 2008 to less than 290,000 in 2012. Second, the product offering increased over this time frame, with 260 models available in 2008 ,and more than 380 models available in 2012. Third, while vehicles grew larger, fuel economy also improved. In addition, Bai et al. (2019) document a remarkable quality upgrading in China's auto industry during the past decade. These patterns suggest that the vehicle market was undergoing significant changes. Forward-looking consumers thus may choose to delay their purchases to take advantage of more choices and lower prices adjusted for quality.

Income is the most important determinant in vehicle purchase decisions. However, income data at the household level in China is not publicly available. Instead, we obtain income distribution in each city in each year as follows: First, we obtain the average income by income quartiles in each city in each year from the statistical yearbooks. Second, we use the Chinese Household Income Survey (2002), together with the aggregated income distribution information, to construct the household income.[15] We adjust the income in the household survey proportionally and separately for each quantiles so that the interpolated income distribution in a given year is consistent with the annual income statistics from the yearbooks.

We also obtain an additional household survey data that contains information about car ownership and household demographics. The survey was conducted by the National Information Center. The data include 1,332 observations in Beijing and 913 observation in Tianjin with rich information on household-owned vehicles, including brand, model, registration date, whether or not was the first time purchase, and replaced car purchase year. There are 759 observations from Beijing and 509 observations from Tianjin in our analysis, and these observations are vehicles buyers who purchased a vehicle between 2008 to 2012. Leveraging the survey data, we are able to generate household shares by four income groups among buyers of new vehicles in each city in each year. Appendix Table 2a presents the shares of different income groups among all households. The table shows that high-income groups account for a disproportionally large share of vehicle buyers. Because the household data allow us to distinguish the first-time buyers from the replacement buyers,

[15]This is a nationally representative survey from the University of Michigan. It has 14,971 observations.

we examine income characteristics of households that fall into these two distinct categories. Appendix Table 2b shows a significant difference of income composition between the first-time buyers and replacement buyers, a distinction that is crucial to identify consumer preference parameters.

3.3 Evidence from Reduced-form Regressions

We first provide some reduced-form evidence on the impact of the lottery policy based on monthly vehicle sales by model in Beijing and Tianjin from 2008 to 2012. Denote m as a market where Beijing is indexed by $m = 1$, j as a vehicle model (nameplate), and t as year-month.

$$ln(S_{mjt}) = \alpha_1 ln(p_{jt}) + \gamma_1 d_{1t} + \gamma_2 d_{1t} \times ln(p_{jt}) + \xi_j + \tau_t + \zeta_{ms} + e_{mtj}, \quad (4)$$

where S_{mjt} is the market share of model j in market m at time t. p_{jt} is consumer price (MSPR plus sales tax) that varies over time but stays constant across cities. d_{1t} is the treatment dummy, which is one for the policy periods for Beijing and zeros otherwise. The coefficient of interest, γ_1 captures the sales impact of the lottery policy in Beijing. We also interact the treatment with vehicle price, $d_{1t} \times ln(p_{jt})$ and let the coefficient γ_2 capture the heterogeneous impacts on vehicle sales. The regression controls for vehicle model fixed effects ξ_j, time fixed effects τ_t, and city-segment fixed effects ζ_{ms}.

Table 2 presents estimation results for four specifications. The base group is Tianjin, and the base year is 2008. The first specification uses the data from the period (2008-2010) before the policy had begun to examine the common trend assumption between the two cities.[16] The equation we estimate is very similar to equation 4 except that we replace those interactive terms with city-year fixed effects, and use the data from pre-policy periods only. The coefficient estimates on city-year interactions are economically small and insignificant, suggesting that the two cities share similar time trends before the policy. The first column in specification 1 uses OLS, while the second column uses instruments for the price variable by the 2SLS. The instruments are based on the sales tax relief policy that was implemented in 2009 and 2010 by the Chinese government. The policy provided purchase tax relief for vehicles according to the engine size, resulting in a discount of 50% in 2009 and 25% in 2010 for displacements lower than 1.6L. The identification assumption is that the discount policy affects only the prices, and the instrument constructed from the policy is uncorrelated with unobserved product attributes. The assumption should hold as the tax relief is based on the engine size which is controlled by vehicle model fixed effects in the regression. The estimates of the price coefficient reduce from -5.23 in OLS to -7.85 in 2SLS, consistent with the finding in the demand literature that unobserved product attributes tend to bias the price coefficient

[16] Li (2017) shows the validity of common trend assumption across four cities including Beijing, Tianjin, Shanghai and Nanjing.

toward zero.

The next three specifications estimate the sales impact of the program using 2SLS. The second specification shows that the lottery policy has reduced sales in Beijing by 61.2% in 2011, and by 49.6% in 2012. This implies that if the lottery policy had not been implemented the number of vehicles sold in Beijing would have reached about 800,000 in 2011, and about one million in 2012, while the observed sales were 327,000 and 505,000 in these two years. By contrast, the number of lottery participants grew from 180,000 in the first month of 2011 to over 820,000 by December 2011, and reached more than 1.34 million in December 2012.

The comparison between the unmet demand and the observed size of the lottery pool implies that the large increase in the number of lottery participants cannot be explained solely by the increase in underlying vehicle demand. Rather, the policy has led potential buyers to participate in the lottery pool earlier than when they need a vehicle, and these participants account for about one million out of the 1.34 million lottery participants in December 2012. The changes in the intertemporal decisions of these participants could not only lead to welfare loss among themselves but also excerbate welfare loss by reducing the probability of winning for those who would have bought a vehicle in the current period. The structural estimation below aims to quantify these welfare impacts.

The third specification includes interaction terms between the treatment dummy and the price variable. The coefficient estimates on those interactions are statistically significant. The estimates suggest that the policy has less of an impact on sales of high-end vehicles than those of low-end vehicles. High-income households are more likely to participate in the lottery, and they are also more likely to purchase the expensive vehicles. Taking this heterogeneity into account suggests that vehicle sales would have reached approximately 750,000 in 2011 and 1.2 million in 2012 had the lottery policy not been in place. These sales figures remain below the number of lottery participants in both years.

Although the policy was announced unexpectedly on December 23, 2010, nine days before the policy started, many households rushed to buy a vehicle within that time, leading to a spike in vehicle sales in December 2010 even after controlling for seasonality. The fourth specification drops the observations from the last two months before and one month after the lottery policy. The estimates are very close to those from specification three.

4 Model and Estimation

In this section, we first lay out our structural model of dynamic demand for licenses and vehicles and then discuss our estimation strategy.

The market has a finite number of licenses to be allocated and a finite number of vehicle models available in each period. Vehicle characteristics and availability change over time. Licenses are identical and are allocated via lottery. One license is needed in order to purchase one vehicle. Vehicle owners can use the existing license to buy a new vehicle only after scraping the used vehicle. Licenses are not transferable and can only be used by the lottery winner. Households discount future utilities at rate β, and receive utility from at most one car in a period. We only focus on the sales of new vehicles and vehicle resales are not considered in our model.[17]

Our model separates households' decision into two stages and assumes that households face an infinite-horizon dynamic decision problem in each stage. That is, a household first chooses whether or not to enter the lottery. If the household wins the lottery, it then chooses a specific vehicle model to purchase. Formally, let J denote the set of available vehicle models. The two-stage decision problem is stated as follows:

Stage I *(Lottery Participation)*: A non-owner decides whether or not to enter the lottery. Before winning the lottery, he faces the same decision problem in every period. After winning, the non-owner becomes an eligible vehicle buyer.

Stage II *(Vehicle Buying)*: The eligible vehicle buyer either chooses a vehicle model, $j \in J$, to buy, or chooses an outside option (i.e., not purchasing). An existing vehicle owner enters the second stage directly, because she can regain the license by scrapping a vehicle already in possession.

Several rationales underpin the two-stage model. First, the model allows potential lottery participants and potential vehicle buyers to represent different groups of households. Potential lottery participants are non-owners, while potential vehicle buyers consist of lottery winners and existing vehicle owners who would need to scrap their existing vehicles.

Second, the two-stage model permits changes in the size and composition of potential lottery participants and vehicle buyers. This is because non-owners in each period endogenously participate in the lottery. After winning, they leave the lottery pool, and become eligible vehicle buyers. Failing to control for this selection will bias the estimates of households' preference and, thus, their willingness to pay for the license and vehicles.

Finally, the two-stage model reflects the fact that, in reality, households in the first stage value the license based on their anticipation of future utilities received from vehicles. The vehicle they will purchase after winning is either not currently available or not in the same quality level as the contemporaneous models. Ignoring this will lead to misspecified future utilities that enter into the willingness to pay for license.

[17]This assumption implies that a household will receive zero scrap value from replacing the old vehicle.

4.1 Demand Model

In this subsection, we specify the lottery participation and vehicle purchase decisions of one household. We discuss aggregating across heterogeneous households in the next subsection.

The household starts as a non-owner. At the beginning of each period, the household chooses whether to enter the lottery. The lottery winners are drawn with equal probability from the lottery pool at the end of each period, so that a winner is eligible to purchase a vehicle from the next period.

Flow Utility Specification

To formalize payoffs, we first specify the set of choices sets, and we designate the relevant state variables. In each period t, the household in the first stage chooses between two options (i.e, whether to participate in the lottery). In the second stage, the household's set of choices includes the new vehicle models that are available in period t and an outside option. The set of available models is denoted as J_t. The state variables are payoff-relevant variables of the lottery mechanism. Those variables include the current and expected future probability of winning and opportunity costs of participating. We denote this set of variables as Φ. The state variables should also include payoff-relevant variables of vehicle market and household's characteristics, the set of which is denoted as S. Market-level variables include the number of models, current product attributes, and any other market characteristics that may influence future model attributes. Household's characteristics include its income level and households-specific demand for having a vehicle.

The flow utility of the household's decision problem in the first stage depends on the state variables in Φ and expected future utility received from purchasing a vehicle (i.e., state variables in S). Denote the utility received from participating in the lottery as v_{i1t} , and denote the utility received if not participating as v_{i0t}. These are specified as the following:

$$v_{i1t} = \pi^e V_{it}^0(S_{it}, \gamma) + \eta_t + \omega_{i1}, \tag{5}$$

$$v_{i0t} = \omega_{i0}, \tag{6}$$

where π^e is the anticipated probability of winning. V_{it}^0 is the expected utility received from the second stage conditional on current state variables in S_{it}, and γ is the set of parameters in the utility function. This term represents the license value in the first stage, which is determined by the future utilities households expect to receive from purchasing a vehicle. We further discuss the specification of this term below after we have introduced the household's dynamic optimization problem. η_t represents the opportunity costs of participating in the lottery. Both ω_{i0} and ω_{i1} are idiosyncratic errors that are mutually independent. They are also independent across time and households with the Type I extreme value distribution with unit variance.

In the second stage, the household that is eligible for purchasing chooses whether or not to buy a vehicle. If a vehicle is purchased, a household receives a flow utility denoted as u_{ijt} for that period and all the following periods, and an one-shot *disutility* from paying for the vehicle price p_{jt} in the period of purchase. If the household decides not to purchase a vehicle, the household receives a utility of u_{ikt}, where the subscript k denotes the model currently owned ($k \in \cup_{s<t} J_s$) or the outside option ($k = 0$) for non-owners.

Let X_{jt} and ξ_j denote observed and unobserved vehicle attributes, respectively. The flow utility that a household receives from purchasing a vehicle $j \in J_t$ is:

$$u_{ijt} = \bar{u}_{ijt} + \kappa_{it} + \varepsilon_{ijt}, \tag{7}$$

$\bar{u}$ is a deterministic component of the utility. It is a function of vehicle characteristics, household demographics and a vector of parameters associated with consumer tastes. As a departure from BLP-style models in the literature, we specify two idiosyncratic shocks that are additive to the utility function and unobservable to econometricians: κ_{it} is serially correlated but independent across households, while ε_{ijt} is i.i.d. across both time and households. We assume ε_{ijt} to follow the type I extreme value distribution with unit variance.

The persistent demand shock, κ_{it}, captures the utility from vehicle ownership itself and is invariant across contemporaneous vehicle models. It represents the changing vehicle need of a household, and captures important dynamic considerations of the household in the lottery participation stage. That is, a household might self-select into the lottery pool because it expects that κ_{it} is large in the future. We specify the deterministic utility as:

$$\bar{u}_{ijt} = X_{jt}\alpha_i^X + \xi_{jt}, \tag{8}$$

where α_i^X is the individual taste of vehicle characteristics and it is a function of unobserved household demographics captured by v_i, which is assumed to follow a standard normal distribution. α_i^X is defined as:

$$\alpha_i^X = \bar{\alpha}^X + \sigma^X v_i.$$

The household that chooses to not purchase a vehicle at time t receives $u_{ikt} = \bar{u}_{ikt} + \mathbf{I}(k \neq 0)\kappa_{it} + \varepsilon_{i0t}$,where $\bar{u}_{ikt}$ represents the flow utility from the model currently in possession. $\mathbf{I}(k \neq 0)$ is the indicator function and equal to 1 if $k \neq 0$, and ε_{i0t} is the idiosyncratic error which is also i.i.d. across time periods and households, and following the type I extreme value distribution. If $k = 0$, the flow utility $\bar{u}_{ikt} = 0$ or otherwise, the current flow utility $\bar{u}_{ikt}$ is determined by the characteristics of model k which was purchased in the past periods. That is, u_{ikt} is defined as in equation 8 using $X_{kt} = X_{k\hat{t}}$, where $\hat{t}$ is the period when model k was purchased.

Dynamic Optimization

Consider now the consumer dynamic optimization decision in both stages. At time t, the household in the first stage faces a decision of whether to enter the lottery or wait until next period. In choosing to participate the lottery, the household incurs an opportunity cost of participating, and it also receives an expected utility from the lottery. The expected utility is a weighted sum of two utilities: (i) an utility from the second stage weighted by the probability of winning; (ii) a continuation payoff that is equal to the utility received if not participating, multiplied by the probability of not winning. The optimal decision, conditional on current states, is given by the following value function (by compressing the time index t and denoting X' as the next-period value of the state variable X):

$$EW(S_i,\Phi_i) = \mathbb{E}\max\left\{\begin{array}{c} \pi^e V_i^0(S_i,\gamma) + (1-\pi^e)\beta\mathbb{E}\left[EW(S_i',\Phi_i')|S_i,\Phi_i\right] + \eta + \omega_{i1} \\ \beta\mathbb{E}\left[EW(S_i',\Phi_i')|S_i,\Phi_i\right] + \omega_{i0} \end{array}\right\}. \tag{9}$$

In the second stage, a first-time buyer makes an optimal decision given his tastes, current income level, persistent demand shocks, available model choices, and vehicle characteristics. An existing vehicle owner can make a replacement decision based on the same set of information except that the outside option is the current vehicle model in possession. Formally, the life time utility of a household i that owns a vehicle $k \in \cup_{s<t} J_s$ or the outside option $k = 0$ is defined by the following value function:

$$EV(\bar{u}_{ik},S_i) = \mathbb{E}\max\left\{\begin{array}{c} \bar{u}_{ik} + \mathbf{I}(k \neq 0)\kappa_{it} + \beta\mathbb{E}[EV(\bar{u}_{ik},S_i')|\bar{u}_{ik},S_i] + \varepsilon_{i0}, \\ \max_{j'\in J_t}\left\{u_{ij} - \alpha_i^P ln(p_j) + \beta\mathbb{E}[EV(\bar{u}_{ij},S_i')|\bar{u}_{ij},S_i] + \varepsilon_{ij}\right\}, \end{array}\right\} \tag{10}$$

where p_j is the tax-inclusive price of product j and α_i^P denotes the individual disutility for price. S_i is the information set of a consumer that affect utility or value of waiting. Specifically, it includes current individual characteristics such as the vehicle need, κ_{it} and incomes, and market characteristics such as vehicle attributes, prices and model availability. We define a household's disutility for price to be a function of income. α_{it}^P is defined as:

$$\alpha_{it}^P = \bar{\alpha}_0^P + \bar{\alpha}_1^P lny_{it} + \sigma^P \nu_i^P, \tag{11}$$

where y_{it} denotes the income level, ν_i^P has a standard normal distribution and σ^P is the standard deviation. We do not use the same term of price preference as in BLP and Petrin (2002) [18] because the median vehicle price in China is higher than the average annual income of most households. The above specification leads to an intuitive pattern that more expensive products have less elastic demand (Li, 2017).

To reduce the computation burden from the large numbers of state variables in equations 9 and 10, we further simplify the state space by defining two inclusive values (by compressing the time index t):

$$\phi_i = \pi^e V_i^0(S_i,\gamma) + (1-\pi^e)\beta\mathbb{E}\left[EW(S_i', \Phi_i')|S_i,\Phi_i\right] + \eta. \tag{12}$$

$$\delta_i = \ln\left(\sum_{j\in J_t} exp(\bar{u}_{ij} + \kappa_i - \alpha_{it}^P ln(p_j) + \beta\mathbb{E}[EV(\bar{u}_{ij}, S_i')|\bar{u}_{ij}, S_i])\right). \tag{13}$$

The inclusive value ϕ_{it} represents the expected utility received from entering the lottery. The logit inclusive value,δ_{it}, is the maximum expected utility a household will receive from buying one of the J_t vehicles. To replace state space with these two inclusive variables, we follow GR, Schiraldi (2011) and Lee (2013) to assume that ϕ_{it}, δ_{it} and κ_{it} are sufficient statistics for determining the probability distribution of future individual preferences and market characteristics conditional on S_{it} and Φ_{it}.

Assumption 3. *Households perceive that the pair of inclusive values* (δ_{it}, ϕ_{it}) *can be summarized by a first-order Markov process:*

$$G(\delta_{it+1}, \phi_{it+1}|S_{it}, \Phi_{it}) = G_i(\delta_{it+1}, \phi_{it+1}|\delta_{it}, \phi_{it}).$$

This assumption helps to simply the dynamic decision problem in the first stage, because both state variables in S_{it} and Φ_{it} in this stage can be replaced by the inclusive values δ_{it} and ϕ_{it}. That is, instead of following the evolution of expected winning probability, participation costs, and vehicle market characteristics, assumption 3 allows researchers to keep track of the market state δ_{it} and lottery state, ϕ_{it} only. Based on assumption 3 and equation 12, we can rewrite households' expected value function 9 as follows:

$$EW(\delta_{it}, \phi_{it}) = \ln\left(exp(\phi_{it}) + exp\left(\beta\mathbb{E}\left[EW(\delta_{it+1}, \phi_{it+1})|\delta_{it}, \phi_{it}\right]\right)\right). \tag{14}$$

In the second stage, only the information set S_{it} is pay-off relevant, but there is an additional state variable κ_{it} that is relevant to the dynamic decision at this stage. To reduce the number of state variables in this set, we make another assumption as follows:

[18] BLP and Petrin (2002) use $ln(y_i - p_j)$ and interpret it as the utility from the composite good.

Assumption 4. *Households in each market perceive that inclusive value δ_{it} and κ_{it} can be summarized by a first-order Markov process:*

$$F(\kappa_{it+1}, \delta_{it+1}|S_{it}) = F_{\delta_i}(\kappa_{it+1}, \delta_{it+1}|\kappa_{it}, \delta_{it}).$$

Similar to assumption 3, assumption 4 helps to reduce the number of state variables relevant to the dynamic decision in the second stage. Although it is hard to specific a proper supply model consistent with the assumption, GR notes that this assumption can be considered approximating boundedly rational households that use only a subset of the data available to them in forming their expectation. Based on assumption 4 and equation 13, we can write the consumer's expected value function as:

$$EV_i(\bar{u}_{ij}, \kappa_{it}, \delta_{it}) = \ln\left(exp(\delta_{it}) + exp\left(u_{ijt} + \beta\mathbb{E}\left[EV_i(\bar{u}_{ij}, \kappa_{it+1}, \delta_{it+1})|\bar{u}_{ij}, \kappa_{it}, \delta_{it}\right]\right)\right). \tag{15}$$

Value of License

We now turn to the specification of function V_{it}^0 that represents the value of a license. A winning license is valid for T periods (in practice6 months) after winning. That is, if a winner fails to purchase any vehicle within that period, the license will expire from the $T+1$ period after winning. We further assume that a winner leaves the market if he/she let the license expire. Based on these assumptions, we write V_{it}^0 as a finite sum of expected utilities of optimized vehicle purchasing decisions, which is:

$$V_{it}^0 \equiv \max_{a_{t+1}\cdots a_{t+T}} \gamma \cdot \sum_{s=1}^{T} \beta^s E\left[a_{t+s}\delta_{t+s}|\kappa_{it}, \delta_{it}\right], \tag{16}$$

where a_{t+s} is a binary variable representing the choice of purchasing at period $t+s$. Parameter γ reflects how the household perceives the anticipated present-discounted utilities received from optimized decisions in the second stage. Unlike the discount factor β, which represents the level of patience and is always between zero and one, γ can be greater than one because it measures the level of impatience over when to enter the lottery. Specifically, the household is impatient if $\gamma > 1$ because the option value of buying a vehicle is inflated by the parameter in the utility received from entering the lottery. In other words, the larger γ is, the more likely households are to enter the lottery even when they expect to receive a little from purchasing vehicles if winning a license. In that case, the lottery mechanism changes the intertemporal decisions and misallocates the licenses.

The license value also depends on households' expectation on the realization of future market state, δ_{it+s}. As implied by the theory model in Section 2, households expecting to receive a larger utility from vehicle ownership in the future is likely to enter the lottery early for the purpose of maximizing the probability of winning at the time when δ_{it+s} becomes substantially large.

4.2 Aggregation and Equilibrium

We first discuss the aggregation of household choices under two scenarios - with and without the lottery policy. We then discuss the probability of a consumer entering the lottery and the aggregated lottery participation rate. Finally, we define the equilibrium of the market.

In each period t, the conditional probability that consumer i owning vehicle $k \in \cup_{s<t} J_s \cup \{0\}$ purchases model $j \in J_t$ is

$$s_{it}^{jk} = \frac{exp(u_{ijt} - \alpha_{it}^{P} ln(p_j) + \beta E[EV(\bar{u}_{ijt}, \kappa_{it+1}, \delta_{it+1}) | \bar{u}_{ijt}, \kappa_{it}, \delta_{it}])}{exp(EV(\bar{u}_{ikt}, \kappa_{it}, \delta_{it}))}. \tag{17}$$

In the pre-policy periods, because the purchases are not constrained by the lottery policy, the aggregation of vehicle demand follows BLP closely. That is, we integrate the choice probability s_{it}^{jk} over the distribution of consumer preferences ν_i and vehicle demand κ_i for each $j \in \cup_{s<t} J_s \cup \{0\}$, and then sum over all existing vehicle models. Let R_t^k be the share of households owning model k (or non-owners if $k = 0$), the market share of product j at time t is:

$$\bar{s}_t{}^j = \sum_{k \in \cup_{s<t} J_s \cup \{0\}} R_t^k \int s_{it}^{jk} dP_\nu^k dP_\kappa^k, \tag{18}$$

where P_ν^k and P_κ^k are the density function of ν and κ integrating over households owning model k or non-owners ($k = 0$) at each period t, respectively.

In terms of aggregation under the lottery policy, we first aggregate individual lottery participation choices. The probability that a household i enters the lottery is:

$$l_{it} = \frac{exp(\phi_{it})}{exp(\phi_{it}) + exp(\beta E[EW(\phi_{it+1}, \delta_{it+1}) | \phi_{it}, \delta_{it}])}. \tag{19}$$

Because only the non-owners are required to enter the lottery before purchasing, the potential lottery participants at the initial period of the lottery policy are all non-owners by the end of 2010. The potential participants in the following periods are non-owners who have not won a license in the past periods. Let R_t^0 denote the ratio of potential lottery participants to the market size. The aggregate participation rate is obtained by integrating over preferences of non-owners and their vehicle need κ_i:

$$\bar{l}_t = R_t^0 \int l_{it} dP_\nu^0 dP_\kappa^0. \tag{20}$$

At each period t under the lottery policy, the market share of product j consists of two parts: purchases from the lottery winners, and replacement purchases from existing owners. The owners have valid license plate and can scrap their existing vehicles in order to purchase a new vehicle. Their choice probabilities are defined as in equation 17. For a lottery winner of period τ, her probability of buying a product j in period t is

$$s_{it}^{j0}(\tau) = \frac{exp(u_{ijt} - \alpha_{it}^{P} ln(p_j) + \beta E[EV(\bar{u}_{ijt}, \kappa_{it+1}\delta_{it+1})|\bar{u}_{ijt}, \kappa_{it}, \delta_{it}])}{exp(\delta_{it}) + exp(\max_{a_{t+1}\cdots a_{t+k}} \sum_{k=1}^{T-t+\tau} \beta^k E\left[a_{t+k}\delta_{t+k}|\kappa_{it}, \delta_{it}\right])}, \tag{21}$$

where T is the total length of validation periods of the license plate. Notice that the difference between equation 17 and equation 21 is the denominator. Because a lottery winner is required to apply the license plate to a vehicle within T period, and he leaves the market when the license plate expires, his continuation payoff in each period, if he does not purchase a vehicle, is a finite sum of expected utilities of vehicles maximized over choices of purchasing. Let $\tilde{R}_t^{\tau}$ denote the share of lottery winners in period s who have not purchased a vehicle till period t. The aggregate demand of product j at time t is:

$$\bar{s}_t^j = \underbrace{\sum_{\tau=t-T+1}^{t} \tilde{R}_t^{\tau} \int s_{it}^{j0}(\tau) dP_{\nu}^{\tau 0} dP_{\kappa}^{\tau 0}}_{First-time\ Purchases} + \underbrace{\sum_{k \in \bigcup_{s<t} J_s} R_t^j \int s_{it}^{jk} dP_{\nu}^{k} dP_{\kappa}^{k}}_{Replacement\ Purchases}, \tag{22}$$

The persistent demand shock, κ_{it}, is assumed to be binary valued, with the lower bound normalized to zero. The upper bound of κ_{it} is parametrized by h. In each period, a low-type household becomes a high-type household with the probability denoted as P_i. The high-type household will remain a the high-type for the rest of periods. The transition probability from the low- to high-type household varies by the household income level, and it is defined as:

$$P_{i \in g} = \frac{exp(c_0 + c_{1,g})}{1 + exp(c_0 + c_{1,g})}, \tag{23}$$

where g is the index for the income group to which household i belongs.[19]

The definition of equilibrium for the vehicle market follows GR and Schiraldi (2011). The supply side assumes that vehicle characteristics evolve exogenously, and new models become available according to some exogenous processes. The inclusive values, δ_{it} and ϕ_{it}, evolve according to the following AR(1) processes:

$$\delta_{it+1} = \varphi_{i0} + \varphi_{i1}\delta_{it} + \varphi_{i2}\kappa_{it} + \varepsilon_{it}, \tag{24}$$

$$\phi_{it+1} = \psi_{i0} + \psi_{i1}\phi_{it} + \psi_{i2}\delta_{it} + \zeta_{it}. \tag{25}$$

where ε_{it} and ζ_{it} are independent and normally distributed.

[19] We simulate household income by assuming the household stays in the same income group for all periods. This assumption helps to simplify the dynamics of the model, as the transition probability is fixed and known to each household and the transition process of κ_{it} is stationary.

We define the equilibrium of lottery participation by imposing the rational expectation assumption: households have a common belief on the probability of winning in each period, and the expectation is consistent with the realized winning probability, (i.e., $\pi_t^e = \pi_t$). For the supply of licenses, we assume the number of licenses issued follows an exogenous process.

4.3 Estimation and Computation

We first present an overview of our computation strategy and then provide a discussion on the intuitions underpinning identification. The objective of estimation is to recover the parameters of vehicle demand $\theta_{vc} \equiv \left\{\bar{\alpha}^X, \bar{\alpha}_0^P, \bar{\alpha}_1^P, \Sigma^X, \sigma^P\right\}$ and parameter in the value of license γ.

Computation

As in BLP, our estimation needs to control for unobserved characteristics ξ_{jt} and η_t. The procedure of recovering these unobservables follows GR and Lee (2013) closely. The former combines methodologies of Rust (1987), Berry (1994), and BLP; and the latter introduces an estimation strategy that links different stages of the model, and estimates both stages simultaneously. We also integrate over unobserved state variables with serial correlation by simulation.

To recover the unobservable, we begin by guessing the initial value of mean utilities $\bar{u}_{jt}$, initial value of participation opportunity cost η_t. We then initialize the logit-inclusive value δ_{it} and inclusive value ϕ_{it} for each period t using equation 13 and 12 respectively, and setting continuation payoffs to zeros. We repeat the steps listed in Figure 3 until the convergence of these two variables. We follow slightly a different algorithm to recover unobservables in the pre-policy periods from that in the policy periods. During the pre-policy periods, we update mean utilities of vehicle models, via the contraction mapping method of BLP, using the values that equalize the predicted market shares (equation 18) to observed market shares. For each iteration of the contraction mapping, the optimal purchase decisions are solved to determine the probability of a purchase conditional on vehicle need κ_{it}. The integration over κ_{it} involves solving an integral over all possible histories of unobservables. To address the high dimensionality of the integration, we follow the methodology in Pakes (1986) and Keane and Wolpin (1997) using Monte Carlo simulations to approximate the integrals.[20]

During the policy periods, we update mean utilities of vehicle models by following the same contraction mapping method as in the pre-policy periods, except that we calculate predicted market shares base on equation 22, in which the first-time purchases need to participate in the lottery system to obtain a license before purchasing. The share of eligible first-time buyers during the policy

[20] We first draw a sequence of realizations of κ_{it} for each households according to the transition process defined in equation 23 . We then compute the individual probability of purchase for each history of κ_{it}, and take the average over the simulations.

periods is computed by the lottery participation rate (equation 20) and the observed probability of winning. We also use the contraction mapping algorithm to update the opportunity cost η_t to equate the predicted lottery participation rate to observed participation rate.

Because the dataset contains monthly vehicle sales of 1,769 distinct models (vintage-nameplate) in each city from 2008 to 2012, we would need to find mean utilities of over 42,000 products. To reduce the computational burden, we categorize vehicles into six segments. We set the sales of each segment to be the total sales of vehicles in that group, use averaged value for the continuous characteristics (e.g. price, engine displacement), and use the mode for the discrete characteristics (e.g., seats, doors). Hereinafter, the index j denotes a vehicle segment.

Moment Conditions

We estimate the dynamic model using simulated generalized method of moments (GMM) based on four sets of moment conditions. We bring market/city index m into our discussion as we leverage data in two cities for estimation. Following Li (2017), the first set of moment conditions is formed based on the common trend assumption underlying the DID framework. That is, the unobserved demand shocks in Beijing and Tianjin would follow the same trend in the absence of the policy. The pre-policy analysis in Section 3.3 shows that that vehicles sales in Beijing and Tianjin track each other very closely before the policy, suggesting that the trend would likely have continued to be similar without the policy. To form moment conditions based on this assumption, we decompose the time varying unobserved demand shocks, ξ_{jmt}, as follows:

$$\xi_{jmt} = \xi_{j,yr} + d_t + d_{jm} + \theta_m yr_t + e_{mtj}, \tag{26}$$

where $\xi_{j,yr}$ is unobserved product characteristics that do not vary within a year and across markets. The time (month) and city-segment fixed effects, d_t and d_{jm}, capture time-invariant and city-specific preferences for different vehicle segments. The parameter interacts with yr_t, θ_m, captures city-specific time trends. e_{mtj} is the residual of ξ_{jt} after controlling for these fixed effects and time trends. Because Beijing implemented the lottery in 2011 and 2012, and Tianjin did not, this assumption implies that the lottery policy is exogenous to the time-varying demand-shocks. Denoting d_{mt} as city-year dummy variables, the first moment condition is:

$$E\left[e_{mtj}|d_{mt}\right] = 0. \tag{27}$$

Although we do not explicitly model the supply side of vehicle market, we allow firms to endogenously set vehicle prices. That is, firms are assumed to observe all product attributes (including ξ_{jmt}) before setting the prices of their products. This leads to price endogeneity since prices would be correlated with unobservable product attributes ξ_{jmt}. To address the price endogenity, we construct a moment condition that is based on a tax policy to encourage the purchase of vehicles of small displacement. The Chinese government provided purchase tax relief for vehicles with displacement of lower than 1.6L by 50% in 2009, and by 25% in 2010. The second set of moment conditions based on this policy is:

$$E\left[e_{mtj}|Z_{jt}^{1.6}\right] = 0, \tag{28}$$

where $Z_{jt}^{1.6}$ is equal to the number of vehicle models with displacement less than 1.6L in segment j and $t \in \{2009, 2010\}$. We defer more discussions on the identification assumptions of implementing this instrument in the next subsection.

The third set of moment conditions is constructed based on the aggregate information from the household survey presented in the Appendix Table 2b. We match predicted shares of households by income group by city among new vehicle buyers, first-time buyers and replacement buyers to those in the table. We set four income groups and use the fourth group as the base group. The moment conditions are:

$$E_t[\bar{s}_{mgt} - s_{mgt}] = 0, \tag{29}$$

where g is the index of income group and $\bar{s}_{mgt}$ is the predicted share of households in income group g among vehicle buyers.

The fourth set of moment conditions is based on the opportunity costs of participating in the lottery, η_t defined in equation (5). We assume η_t as a stochastic variable that follows an AR(1) process. The error term of this process, ς_t, is defined as:

$$\varsigma_t = \eta_t - \lambda_0 - \lambda_1 \eta_{t-1}. \tag{30}$$

We assume that ς_t is not correlated with the observed winning probability and vehicle characteristics, which is included in Z in the fourth set of moment conditions below.

$$E\left[\varsigma_t Z_t\right] = 0 \quad \text{and} \quad E\left[\varsigma_t \triangle Z_t\right] = 0. \tag{31}$$

Identification

Identifying the discount factor in a dynamic discrete choice model is notoriously difficult (Rust, 1994) and we assume the same discount factor in both stages, $\beta = 0.90$. There are key identification issues. First, we need to control for unobserved product attributes (e.g., quality) in order to identify the price coefficient α^P. Second, we need to separately identify household cross-sectional heterogeneity on vehicle preference, captured by random coefficients σ^X, from household inter-temporal heterogeneities, governed by the persistent vehicle demand shock κ_{it} and income coefficients, using only market-level data. Finally, we need to identify the parameter γ that governs households' perceived value of a license V^0 (defined in equation 16).

The price coefficient α_P consists of three parameters as defined in equation 11. $\bar{\alpha}_1^P$ captures the degree of preference heterogeneity on price due to variation in income. We identify this parameter using the set of micro-moments defined in equation 29. Each moment matches predicted to observed shares of purchases by households belonging to a same income group. Table 2a illustrates that high income-groups accounts for disproportionally larger shares among all vehicle buyers, implying a positive estimate for this parameter. The additional preference heterogeneity on price is captured by a random coefficient in α_{it}^P that follows a normal distribution. We rely on the time-series variation of price and temporal variation of market shares to identify the parameters that govern the distribution of this random coefficient. Heuristically, the change in market share of a vehicle model j associated with a change in its price over time identifies the mean $\bar{\alpha}_0^P$. The relative change in market shares of the other models in response to model j's price change identifies the standard deviation σ^P. Because of the heterogeneity in price preference, a change in price of model j leads to unequal proportion change in market shares of other models. The degree of unequal change that is not explained by income heterogeneity will help us to identify the standard deviation σ^P.

As mentioned in the previous subsection, we address price endogenity using the price variation from tax reliefs on vehicles of small engines in 2009 and 2010 as in equation 28. The identification assumption is that the tax relief policy is an exogenous shock that affects consumer choices only through vehicle prices. Because the tax relief is based on the engine size which is controlled by vehicle model fixed effects as in equation 26, the instrument constructed based on this policy $Z_{jt}^{1.6}$ should be uncorrelated with the econometric error term e_{mjt}. The reduced-form regression in Section 3.3 (Specification 1) using the same policy as an exogenous shock to price shows that the 2SLS estimate is larger in magnitude than the OLS estimate for the price coefficient.

Two parameters are associated to the distribution of persistent demand shock κ: the upper bound of its support and a transition probability. The upper bound, h, is identified from the difference in income composition between the first-time and replacement buyers. The demand shock κ_{it} is invariant across contemporaneous models and only enters into non-owners' utilities if a vehicle is purchased; whereas for owners, κ_{it} always enters into their utilities regardless of their choices. Thus, κ_{it} can only affect non-owners' choice margin of purchasing a vehicle in response to changes in their incomes. If h is large, non-owners of the high type will be more likely to purchase a vehicle even when their income is low, while the probability of replacement purchase depends on households incomes only. Therefore, when κ_{it} is large, the proportion of lower income households among first-time buyers should be higher than that among replacement buyers. On the contrary, when κ_{it} is small, the first-time and replacement buyers are similar in their income levels.

The transition probability of the persistent shock P is identified via time-series variation in vehicle sales. If the probability that a household becoming a high-type is large - as would be the case if a great proportion of households became urgent buyers in the early periods - a rapid growth of vehicle sales should be observed in the early period, rather than in later periods. A relative smooth growth in sales would indicats that the probability that households make a transition to the high type is moderately small.

Finally, the identification of γ in equation 16 comes from the variation in lottery participation rates. Variation in lottery participation is affected by changes in license values defined in equation 16. It is determined by the anticipated market states, captured by the inclusive values, within the next T periods. The degree to which the lottery participation rate changes as the market states change over time identifies the level of impatience of households in deciding when to enter the lottery.

5 Estimation Results

We first present the parameters estimates from the structural model and robustness checks. We then discuss the implication of the results.

5.1 Parameter Estimates from the Dynamic Demand

Table 3 reports the results for the structural model. The first panel of the table corresponds to parameters in θ_{vc}, which appear in the consumer-specific utility function in equation 7. We do not report the parameters of mean utilities because they are not needed for policy simulations and welfare analysis. The second panel reports parameter estimates for γ, which is the parameter of license plate valuation defined in equation 16. The last panel presents the upper bound of the support of the persistent demand shock. The same panel also reports the estimated probability that the persistent demand shock transits from low to high as defined in equation 23.

We present the structural parameters in five specifications based on different assumptions and estimation strategy. In the first specification, we estimate coefficients using all the moment conditions described in the previous section, and setting income coefficients c_g in equation 23 to zeros. In the second specification we exclude the micro moments constructed through the shares of income groups among buyers. Specification 3 drops the observations in November and December of 2010 and January of 2011 to remove the anticipation effect. Specification 4 assumes away the persistent demand shock κ_{it}. Specification 5 relaxes the assumption that coefficients c_g in equation 23 are zeros. Hence, the transition probability of the persistent demand shock is allowed to vary across different income levels. We take specification 1 as our baseline model upon which the counterfactual simulations are based. Other specifications serve as robustness checks.

In the baseline model, the coefficient estimate on $ln(price)$ is significantly negative, while the coefficient estimate on interaction between this price variable and $ln(income)$ and that on income variable alone are both positive. This suggests that households dislike higher prices, whereas those with a higher income are less price sensitive. In addition, the inclusion of $ln(income)$ in the utility function allows the difference between a new vehicle and the outside option to differ by income. A positive coefficient on this variable implies that the likelihood of a consumer purchasing a new vehicle increases with income.

We include two random coefficients into our model, one on price and the other on the constant term. The last two coefficient estimates in the first panel are standard deviations of random coefficients for $ln(price)$ and $constant$ that capture households' heterogeneous preferences. Both estimates are significant in specification 1. The estimated parameter on the $constant$ term is large in magnitude, which indicates more variation in the flow utility from a vehicle.

In the second panel, the coefficient estimate for the parameter in the value of a license, γ, in specification 1 is 19.68, which is significantly greater than one. This indicates that households are impatient when deciding to participate in the lottery. The estimate of this parameter implies substantial dynamic inefficiency costs.

In the last panel, the estimate for h is 3.08 and the estimated transition probability is around 5%. Given that the average flow utility of vehicles is estimated to be around 1.5, the demand shock is significantly large relative to the average utility received from a vehicle. Thus, our model captures two groups of the first-time buyers. The first group consists of households that care more about the product quality and less about the price; the second group consists of households that care less about the product quality and more about price. The latter choose to buy because the persistent demand shock is large (i.e., having a vehicle is important).

Column 2 provides estimates from the dynamic model where the micro-moments on the shares by income groups among buyers are excluded. A comparison with the baseline specification show that the transition probability of the persistent shock κ_{it} does not changed, and the estimate for h changes slightly. This is consistent with the identification intuition that the upper bound of persistent demand shock is identified by matching the micro-moments, while the transition probability is mainly identified by the time-series variations of vehicle sales. Note that excluding those micro-moments also changes estimates for γ because the expected future utilities received from owning a vehicle has changes due to the change in h.

The estimation results from specification 3, in which we dropped observations of the last two months before and one months after the policy began, are very similar to our baseline estimations. Therefore, we find that the anticipation effect and the announcement effect have a less significant impact on the main conclusions, which are drawn from the estimation results.

Column 4 shows the estimates from dynamic model in which the persistent shock is assumed away. Without the heterogeneity driven by this demand shock, the specification renders a large coefficient estimate for income. This is because part of the heterogeneity preference due to the persistent demand shock is captured by the heterogeneity in incomes. The coefficient estimate for γ is also larger in this specification. All these changes indicate the crucial role of including the persistent demand-shock term in our model.

The last column provides transition probabilities of the persistent shock across different income levels. We find this specification yields less appealing results than our baseline specification. Except for the second income group, all transition probabilities are insignificant from zero. In addition, standard errors for the rest of the parameters are also increased in this specification. Therefore, although it is more reasonable to let the transition probability of persistent shock vary across income, this specification is not well identified and we choose specification 1 as our baseline model.

5.2 Price Elasticities

We calculate the dynamic price elasticities based on the first specification under scenarios of permanent and temporary price changes with the assumption that households know the nature of the price change. For the temporary price change, we compute the expectation on δ_{it+1}, ϕ_{it+1} and κ_{it+1} using the baseline δ_{it}, ϕ_{it} and κ_{it} in equations 24 and 25. For the permanent price change, we use realized δ_{it}, ϕ_{it} and κ_{it}. We also assume that the future states of vehicle characteristics, the lottery policy, and value functions - evolve identically in both scenarios, conditional on δ_{it}, ϕ_{it} and κ_{it}.

We compare the sales impact of temporary and permanent price increase of one percent. Figure 4 shows the impact for six segments in May 2010.The sales changes are slightly larger for the temporary price change than permanent one due to the intertemporal substitution from the temporary price change. The difference is more salient for the mini segment, suggesting that when the vehicles in the mini segment experience an one-percent temporary price increase, some buyers choose to delay their purchase.

The average own-price elasticity for the temporary price change is -9.8 across six segments, which is higher than the estimates in the literature on the U.S. market, where elasticities range from -3 to -8.4 (Berry et al., 1995; Goldberg, 1995; Petrin, 2002; Beresteanu and Li, 2011). This is consistent with what we would expect given that 1) income levels in Beijing and Tianjin are half those in the U.S. over the 1981-1993 data period used in Petrin (2002), and 2) vehicle prices in China are now and were then much higher than the prices in the U.S. for the same brand. However, our elasticity estimates are lower than the static model estimates in Li (2017) using the similar data, which are -10.51 on average and range from -8.70 to -15.97. There are at least two reasons for the difference. First, we estimate the model at the vehicle-segment level rather than at the vehicle-model level. Our estimates do not capture within-segment substitution. Second, static models could overestimate own-price elasticities for not accounting for consumer forward looking behavior. The important features of China's auto industry during our data period is that price are declining while quality and model availability are increasing. Consumers may find it optimal to delay their purchases with a price increase, which reduces sales in the current period. A static model would attribute intertemporal substitution to price sensitivity, and overestimate the own-price elasticities.

5.3 Other Implications

To examine the sources of heterogeneity, we plot the evolution of the logit inclusive value, δ_{it}. Figure 5 depicts δ_{it} from the first specification for six sets of consumers with random coefficients at different percentiles of the distribution. Specifically, we set preferences on price and the constant term at the (25th, 25th), (75th, 75th) and (25th, 75th) percentiles of their respective distributions, in combination with the persistent demand shock, κ, at the low or high level.

For each set of consumers, the inclusive value is increasing over time, indicating that households expect a higher utility from buying a vehicle in the future (e.g., due to declining prices and quality upgrading). Therefore, consumers have incentives to delay their purchase. Without taking this into account, a static model could overestimate consumer price sensitivity as discussed above.

Holding κ fixed, the inclusive value for the (25th, 25th) percentile group is far below than that for the (75th,75th) and (25th, 75th) groups, while the value for the latter two groups are very close. This suggests that the heterogeneity in household price sensitivity drives less variation in the inclusive value than that in the flow utilities. That is, the heterogeneity in the constant term is more important in affecting the variation in the inclusive value.

Households in (25th, 25th) percentile groups with a higher demand shock (i.e., high κ_{it}) have a higher inclusive value than those in (75th, 75th) and (25th, 75th) percentile groups before June 2011. That indicates that before June 2011, households with a higher demand shock were more likely to purchase a vehicle than households that with a low demand shock regardless of their preference for price and vehicle ownership (i.e., coefficients on price and the constant term). This suggests that the demand shock plays an important role in our model: it captures exogenous factors (e.g., a change in working location, or an increase in family size) that could be an important part of vehicle purchase decisions.

Figure 6 plots the the inclusive value, ϕ_{it} over time. We set coefficients on price and the constant term at the (25th, 25th) and (75th, 75th) percentiles of their respective distributions. The value increases over time, albeit slowly, as the market improves and the license value increases. Compared to δ_{it}, ϕ_{it} is less heterogeneous. The gap between the values for different groups shrink over time, and converges to zero by the end of the sample period. The result is intuitive. The probability of winning is low and decreases over time. As a result, the expected utility that households expect to receive from participating the lottery decreases over time as well.

We further investigate the assumptions on the transition of the state variables. We fit ϕ_{it} and δ_{it} into a AR(1) process as in equation 24 and 25, respectively. Figures 7 and 8 depict the prediction errors for a household in the 50th percentile for both random coefficients on price and the constant term. Neither figure exhibits serial correlation or change in variance over time. One concern is that the AR(1) process may not be a good approximation to the stochastic processes of ϕ_{it} and δ_{it}. To verify that, we test whether the prediction error is close to a white noise by applying the autocorrelations (ACF) and partial autocorrelations (PACF) tests to the prediction errors of ϕ_{it} and δ_{it}, respectively. The results are plotted in figures 9 and 10. Both figures show the prediction errors are close to a white noise, as the ACF and PACF across different lags are almost zero.

Finally, we study the impact of lottery policy on vehicle sales. Table 4 presents the simulated sales under the counterfactual environment of no lottery policy for the baseline specification and two other alternative specifications. For the baseline specification, the counterfactual sales in Beijing are 1.2 million in 2011 and 1.8 million in 2012. In these counterfactual scenarios, the first-time buyers account for 73% of sales in 2011, and 59% of sales in 2012. Relative to observed sales of 326,769 and 504,990 under the policy, this suggests that lottery policy has reduced sales by 73% (2011) and 72% (2012). Figure 11 plots the percentage of households making a purchase observed in the data, and the counterfactual estimates in the absence of the lottery policy from January 2008 to December 2012 using the baseline specification. The estimated share of households making a purchase matches closely to the data during the pre-policy period, suggesting a good model fit. The alternative models predict similar simulated sales impacts. This is because the policy impacts are mainly identified through the first set of moment conditions that utilize the common trend assumption.

6 Simulations and Welfare

6.1 Counterfactual Simulations

We consider two counterfactual scenarios for Beijing based on the estimates from the baseline specification. In the first scenario we assume that the lottery policy starts unexpectedly from the first month of the sample period (January 2008). In the second scenario, we assume the lottery policy is absent during the sample period. In the first scenario we simulate household decisions on both lottery participation and vehicle purchases while in the second scenario we only simulate household decisions on vehicle purchases.[21] All consumers are assumed to be the non-owners from the first period in both scenarios. Using the same inclusive values that capture the market state and consumer preferences reconciled from the data, we simulate participation costs by using equation 30. We set the winning probability at 1.38% and assume the winning probability to be constant over periods.[22]

The simulation results show that our model is able to replicate the drastic increase in lottery participation that far exceeds the increase in vehicle sales without the lottery policy. Table 5a shows that on average around 50% of total households enter the lottery for getting a license in each month, while in the absence of the lottery policy, the monthly average share of first-time vehicle buyers is less than one percent from 2008 to 2011, and less than three percent in 2012.

To examine the extent to which the lottery policy had induced households to enter the lottery pool early, we compare the time of first lottery participation and that of the first purchase. Table 5b shows that if lottery had started in 2008, most households would have entered the lottery for the first time within the first quarter of that year. Without the policy, however, most of the households would *not* have chosen to purchase a vehicle within five years. Figure 12 plots a histogram showing the duration of time prior to households' first entry into the lottery, and their first vehicle purchases. On average, households move up their lottery participation by at least four years. The probability of winning used in simulations (1.38%) indicates that a lottery participant is likely to wait six years before winning a license. Because the expected waiting period is so long, forward-looking households that plan to buy a vehicle within six years are likely to join the lottery pool much earlier than when they actually intend to buy a vehicle.

Figure 13 shows simulation results of lottery participation, vehicle ownership, and sales with and without the lottery policy in place. The lottery policy reduces both vehicle sales significantly. Had the lottery policy started from January 2008, about 85% of the total vehicle sales in the absence of the lottery policy would be reduced in each month. By comparing the vehicle ownership rate between the scenario where the lottery policy had started in 2008 and the scenario where the policy were absent, the ownership rate with the lottery would not only be lower, but also grow in a much lower rate.

Figure 13 shows that if the lottery policy had not taken in place, the vehicle ownership rate would not reach to 50% until 2012. However, lottery participation rate (the fraction of households that entered the lottery) stays almost constant around 50% over the sample period. The difference between these two shares shows that households participate in the lottery earlier than they would

[21] Independent of the estimation, we separately simulate the decisions of 2,000 households that do not own a vehicle at the beginning of the simulations. Each household is characterized by a vector of income and random draws of unobserved household attributes. For each consumer, we draw a vector of 200 idiosyncratic errors from the Type I extreme value distribution.

[22] We fit the winning probability via an AR(1) process. The limit of the AR(1) process is 1.38 percent.

have purchased a vehicle without the policy. The magnitude of the difference determines the extent of dynamic inefficiency.

Figure 14 provides a 4 by 4 matrix of plots that shows the shares of lottery participation and vehicle purchase under the two policy scenarios. Each plot corresponds to a combination of two preference parameters on income and the constant term. Each parameter is categorized into four groups: below 25%, 25%-50%, 50%-75%, and above 75%. Across the plots, the coefficient on price increases from top to bottom, and the constant term increases from left to right. Two are two important patterns from the plots. First, there is significant differences across the plots in terms of the relationship between lottery participant and vehicle purchase shares. Second, the preference heterogeneity on the constant term (i.e., preference on vehicle ownership) plays a more important role in the difference of the two shares. For the group of households with a weaker preference for vehicle ownership (the constant term less than the 25 percentile), their ownership rate is almost zero without the lottery policy but their lottery participation rate is still around 50%. In contrast, households with a stronger preference for vehicle ownership (the constant term above 75 percentile) have a higher ownership rate without the policy. The ownership rate among this group would catch up with the lottery participation rate within two years from the beginning. This indicates that the dynamic inefficiency is more significant among the households with a weaker preference for vehicle ownership.

Figure 15 demonstrates the accelerated purchase timing that households exhibit under the lottery policy for the lottery winners. It shows the histogram of the difference between the timing of purchasing without the policy and that with the policy, where a positive difference indicates the purchase is moved forward. The distribution shifts to the right with the average being approximately six months and the median being four months. This indicates that on average, lottery winners would move up their purchases by six months. More than half of the lottery winners would buy a vehicle more than four months earlier than they would have without the policy. In contrast to the early participation, early purchasing is a less significant issue. This is due to the rational expectation assumption. Households foresee when they would have purchased a vehicle without the lottery policy, and the length of time that they are likely to wait before winning a lottery. They then optimize the timing to enter the lottery by matching the time that they win a license to the time they actually intend to buy a vehicle. The simulation result indicates that households can generally match the two times closely.

6.2 Welfare Analysis

We use the estimates from the dynamic demand model to examine how the lottery policy affects consumer welfare and the underlying channels. We focus on two types of efficiency impact: static misallocation and dynamic misallocation.[23] We simulate household decisions on lottery participation and vehicle purchase in 2011 and 2012 under the following three allocation scenarios:

(i) First-best allocation. Licenses are allocated to the households with the highest valuations and are hence efficiently allocated. In theory, the first-best scenario could be achieved through an auction system. Therefore, one can use welfare analysis in this scenario to compare welfare differences between the lottery system and a theoretically efficient auction systems.[24]

(ii) Second-best allocation. Licenses are allocated with a uniform probability among households that would purchase a vehicle in a given period (e.g., consumer surplus from vehicle purchase being larger than the outside option) in the absence of the lottery policy. Allocation could be inefficient in that licenses might not be allocated to households with the highest valuations. The source of misallocation is the cross-sectional heterogeneous preferences. The welfare difference between the first scenario and the second scenario is static misallocation.

(iii) Allocation under the lottery policy. As shown in the previous sections, lotteries will not only allocate licenses to households with lower valuation, but also induce households to move their participation forward, exacerbating the static misallocation. We define the additional welfare loss from changes in intertemporal decisions as dynamic inefficiency. As lottery winners are required to purchase a vehicle within a finite period before the license expires and those without doing so are allowed to re-enter the lottery within three years. This policy in turn drives lottery winners to move their purchases forward. To separate the dynamic inefficiency generated by advanced purchasing from the total welfare loss, we simulate purchasing decisions subject to the expiration rule and those without the rule. The difference in welfare outcomes from these two simulations provides the welfare loss from early purchase itself.

We identify an early participant by comparing the time that a household enters the lottery under the lottery policy and the time that the same household would choose to buy a vehicle under the counterfactual scenario of no policy. Similarly, an early purchase is identified through the difference in time that a household purchases a vehicle under the two scenarios (with and without the lottery policy). Table 6 reports the summary statistics of early participation and early purchases. Around 70% of 2011 participants and 44% of 2012 participants were early participants. They moved their participation forward by at least 12 months on average.[25] The lottery policy is likely

[23]Different from Li (2017), we do not consider the external costs associated with vehicle usage post allocation.

[24]In practice, the auction design in Shanghai is unlikely to be efficient. The auction is carried out in two stages where bidders are allowed to modified their bids in the second stage within a narrow band around the lowest accepted bid at that point. The bidding constraints could limit price competition and degrade efficiency as documented in Holt et al. (2013) using lab experiment. Huang and Wen (2019) study the properties of the auction-lottery hybrid system being used in four other cities in China and shows that the system preserves the majority of the efficiency of a theoretically efficient auction system while improving equity.

[25]We are unable to simulate household purchase decisions in absence of the lottery policy after 2012 due to the data limit. But we observe almost 50% of households were still non-owners by the end of 2012 and many of them had previously entered the lottery. For those households, the number of months they have moved forward their decision

to allocate some licenses to early participants rather than to those who would purchase a vehicle in that period even without the policy. Early purchases were around 43% of total sales in 2011, and 25% of total sales in 2012. On average, households moved their purchases forward by at least three months in 2011, and by one month in 2012. The limited difference in purchasing time among lottery winners is due to the rational expectation assumption where consumers time their lottery participation decision based on the winning probability and the time when they need a vehicle. This suggests that the welfare loss from early purchase is likely to be a small part of dynamic efficiency.

We calculate the (expected) consumer surplus for consumers who are predicted to purchase a vehicle in each scenario:

$$CS = \sum_{i,j,t} E\left[\max_{j \in J_t} \frac{\bar{u}_{ijt} + \kappa_{it} - \alpha_{it}^P ln(p_{jt}) + \beta E[EV(\bar{u}_{ijt}, S_i') | \bar{u}_{ijt}, S_i] + \varepsilon_{ijt}}{\alpha_{it}^P / p_{jt}}\right], \tag{32}$$

where ε_{ijt} is the idiosyncratic error term conditional on buying model j. We decompose welfare losses into inefficiencies generated by static misallocation and dynamic misallocation. We further decompose dynamic misallocation into that from early participation and that from early purchase.

Table 7 presents the welfare estimates under the three scenarios in 2011 and 2012. By allocating the license plate efficiently in the first scenario, total consumer surplus would have been RMB 218 billion and the surplus per buyer would have been RMB 163,000. About 75% (RMB 163 billion) of the total surplus under the first-best scenario would have been realized in the second-best allocation, while only 47% (RMB 103 billion) was realized under the lottery policy. These results highlight the substantial efficiency cost of implementing the lottery policy. The lottery policy generates consumer welfare loss of RMB 114 billion during 2011 and 2012. Around 48% of the total welfare loss could be attributed to static misallocation. Over half of the welfare loss (52%) is due to dynamic inefficiency of the lottery policy. With dynamic inefficiency, the welfare loss from early purchase was only RMB 1.2 billion and therefore, the majority of dynamic inefficiency stems from from early participation into the lottery.

7 Conclusion

Using lotteries to allocate scarce resources could lead to misallocation and welfare loss due to the inability of lotteries to allocate the resources to consumers with the highest willingness to pay. When the resources are durable in nature and consumers are forward looking, lotteries could

to participate in the lottery can be measured as the difference between the time of their participation and the end of 2012 (rather than the true future time). Hence, this is a conservative estimate. In the counterfactual analysis in Section 6.1 where started the policy from 2008 instead of 2011, however, we obtain a less conservative estimate which shows that households moved their market participation forward by at least four years.

induce consumers move forward their participation decision, leading to a large pool of participants and reducing the chance of allocating the resource to those with a high WTP. The changes in participation timing represent another channel of welfare loss and leads to dynamic inefficiency.

To the best of our knowledge, this paper provides the first empirical analysis on the misallocation and welfare consequences from lotteries in a dynamic model. In the context of lotteries for vehicle license in Beijing, our analysis suggests that consumers on average participate in lotteries four years earlier than they would purchase a vehicle in the absence of such a policy. The early participation led to the dramatic increase in the lottery pool size and reduces the chance of vehicle purchase for those with a high WTP for a vehicle, leading to significant welfare loss. The dynamic inefficiency accounts for over half of the total welfare loss from the lottery policy.

Although a Pigouvian tax such as congestion pricing that directly targets the externality-generating activities is likely to be more efficient than a blunt policy instrument such as a purchase restriction, several cities in China have adopted vehicle purchase restrictions and more cities may adopt this policy to address severe urban traffic congestion and air pollution. The choice of allocation mechanisms could have important welfare consequences. The findings in our analysis highlight the importance of taking into account consumer forward-looking behavior in the design of allocation mechanisms for durable resources. Although our study focuses on vehicle license allocation, the empirical framework could be employed in other settings for example to study rent control regulations or H1B visa lotteries, and to compare lotteries with alternative allocation mechanisms.

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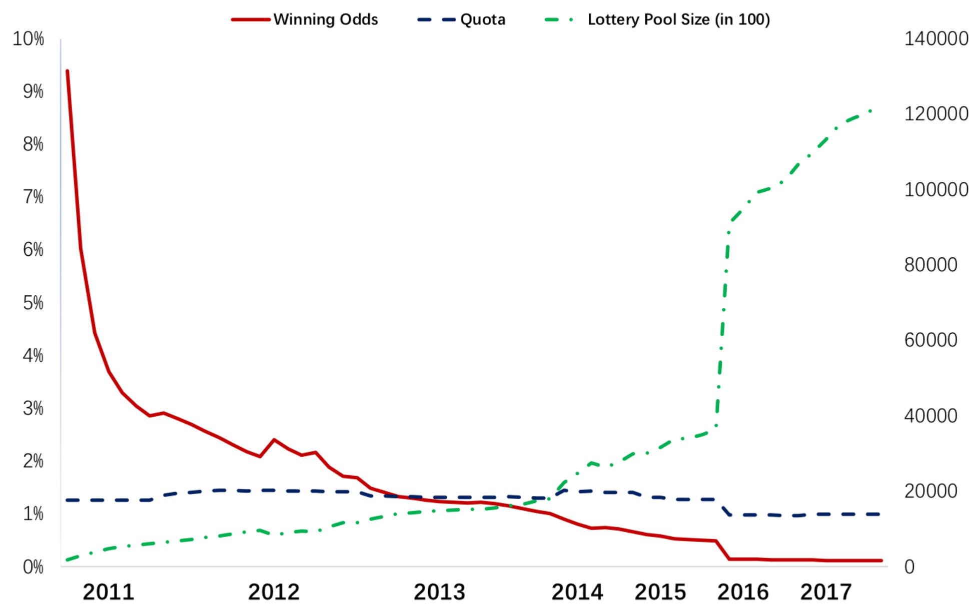
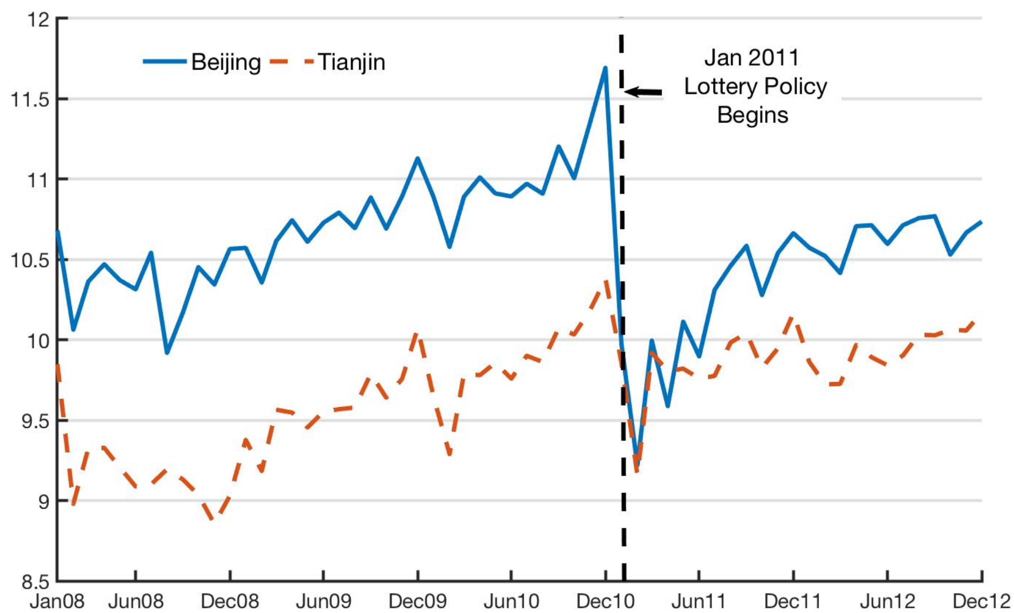
Figure 1: Lottery Winning Odds and Participant Pool Size 2011-2017



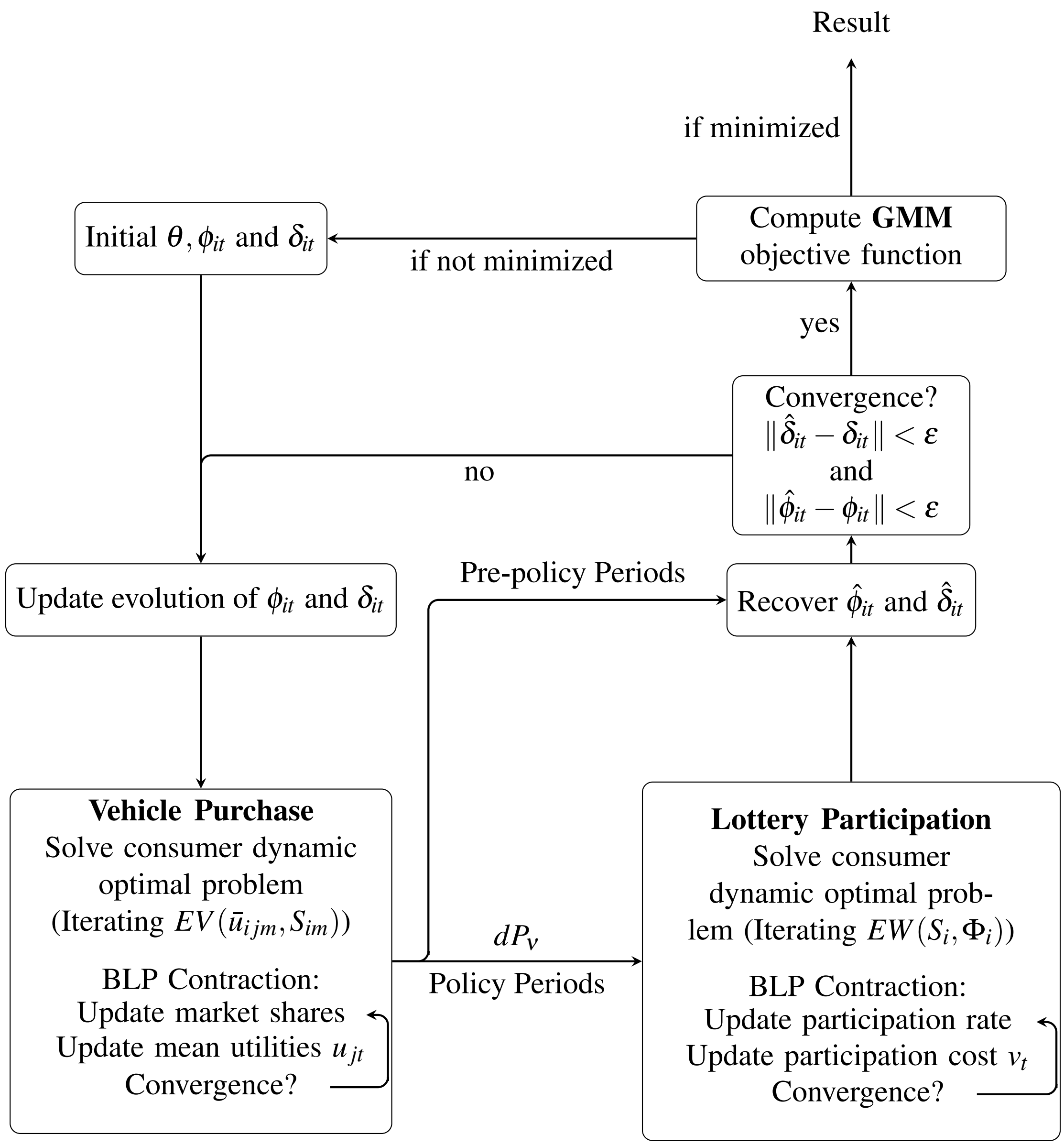
Notes: The y-axis on the left indicates the probability of winning a license and that on the right indicates the quota (the licenses to be issued) and the number of lottery participants (in 100). The lottery was held once every month from 2011 to 2013 and then changed to bimonthly from 2014. In 2011 and 2012 about 20,000 license plates are distributed in each month and the annual cap was reduced over time to 150,000 in 2017.

Figure 2: New Vehicle Monthly Sales (in logarithm) of Cities 2008-2012



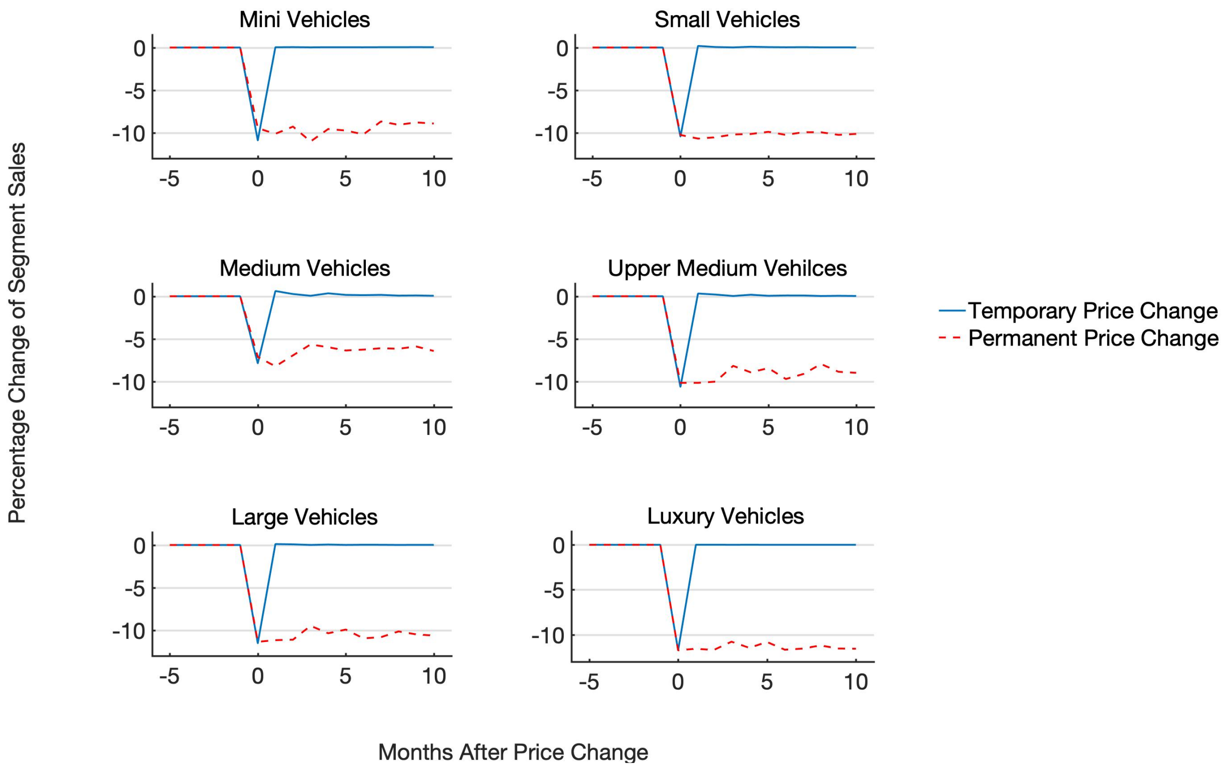
Notes: The y-axis indicates monthly sales (in logarithm) of new vehicles.

Figure 3: Estimation Algorithm



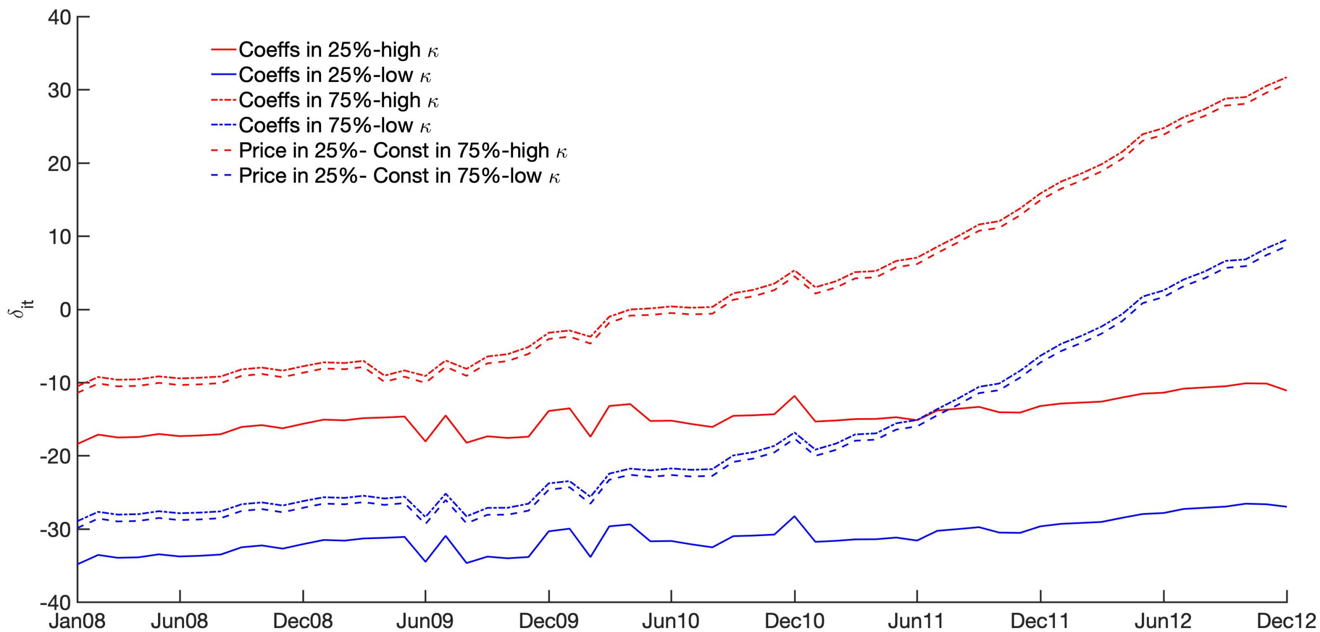
Notes: Computation algorithm for the estimation of dynamic model of consumer demand. “BLP Contraction" refers to the contraction mapping introduced in Berry et al. (1995).

Figure 4: Dynamic Price Elasticities for Segments



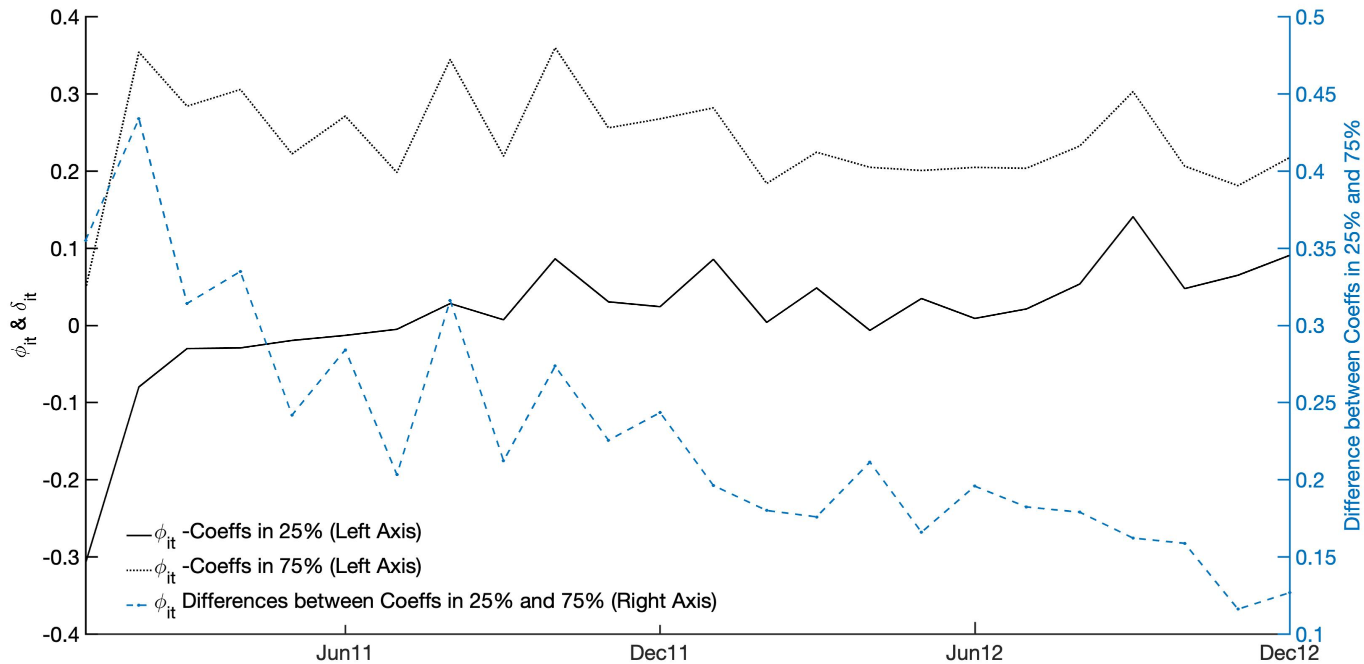
Notes: Price elasticities are calculated by the percentage changes of sales due to an unexpected price increase at time t. Consumers at time t know that the nature of price changes. We set the time t to be May 2010, the middle of our data sample.

Figure 5: Evolution of log inclusive value δ_{it}



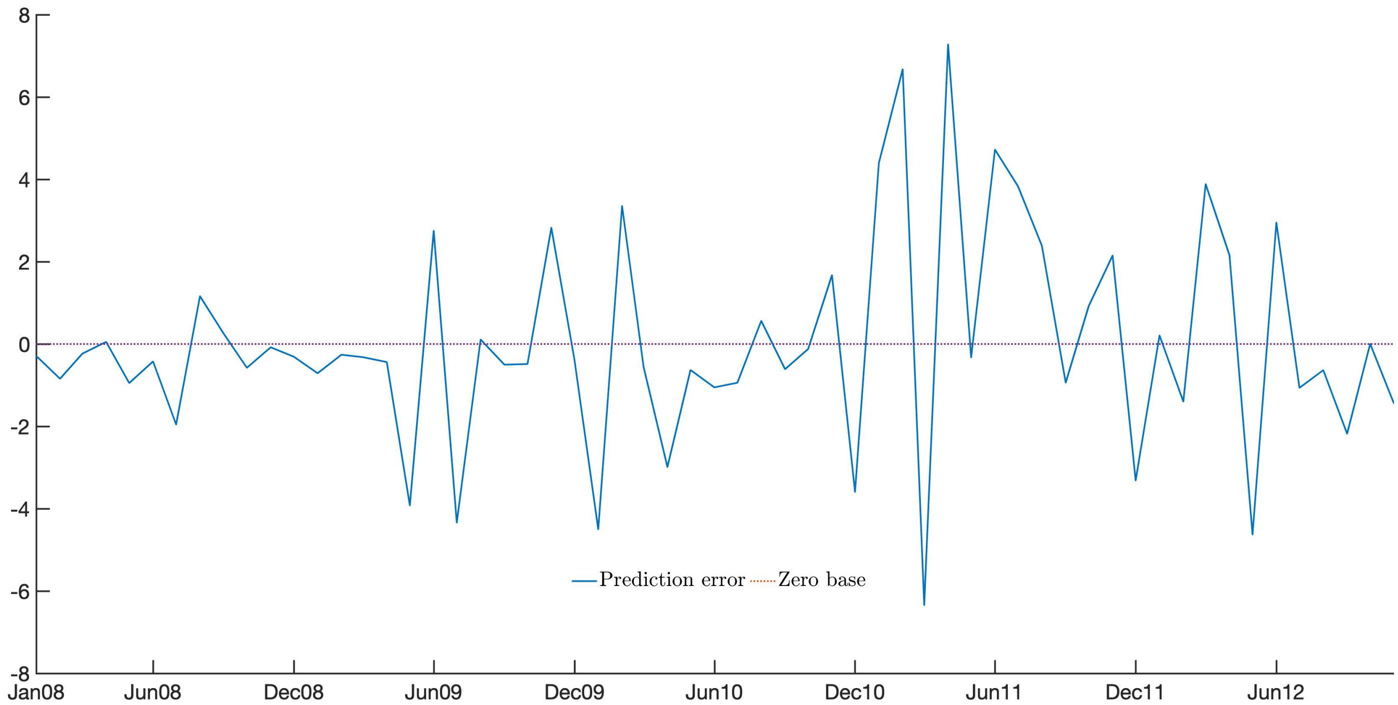
Notes: The y-axis indicates the inclusive value δ_{it}. The six sets of inclusive values plotted in the figure correspond to the six combinations of κ, and the preferences on price and the constant term. κ, the persistent demand shocks, can be at the lower or upper bounds. The preferences on price and the constant term are at (25th, 25th), (75the, 75th) and (25th, 75th) percentiles of their respective distributions.

Figure 6: Evolution of inclusive value ϕ_{it}



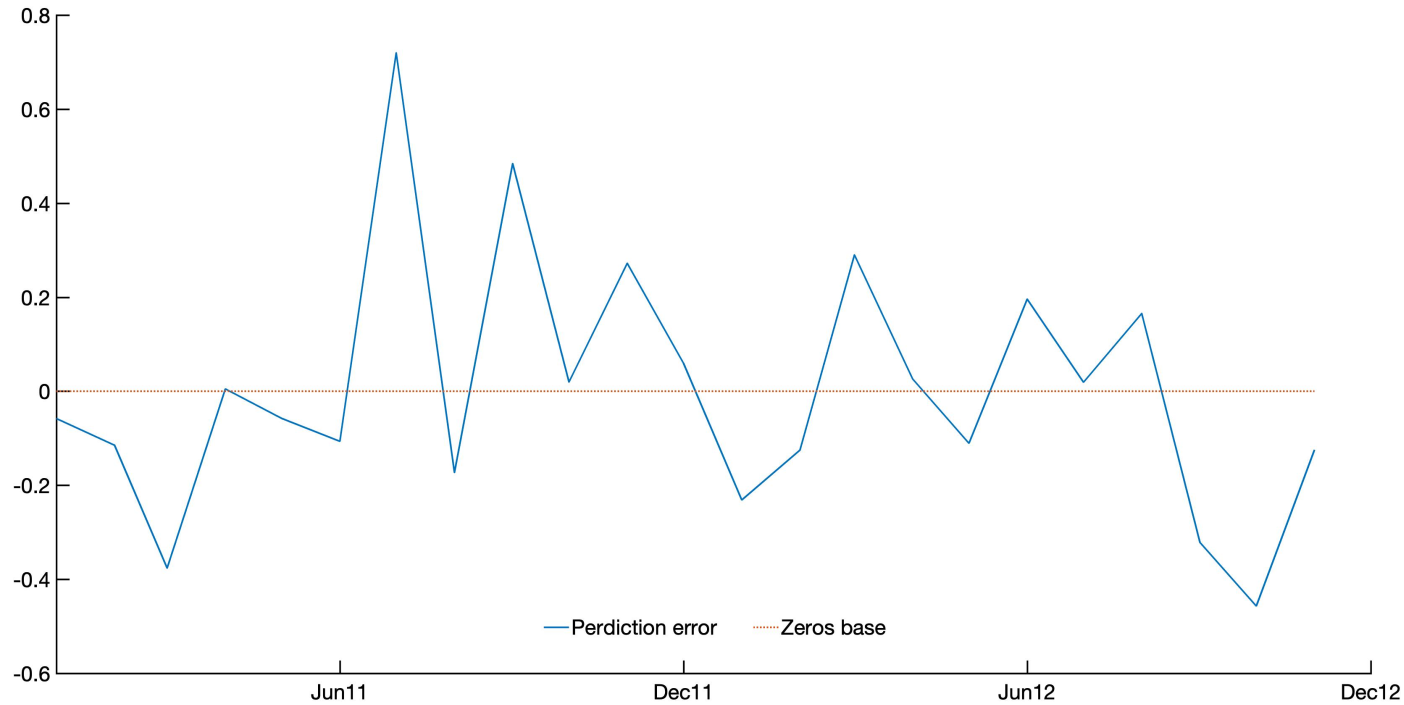
Note: The y-axis on the left indicates the inclusive value ϕ_{it}. Values of two groups of households with price and constant coefficients at the (25þ, 25th) and (75th, 75th) percentiles of their respective distributions. The persistent demand shock, κ, is at the upper bound. The y-axis on the right indicates the difference of the inclusive value ϕ_{it} between the two groups.

Figure 7: Prediction Errors of δ_{it}



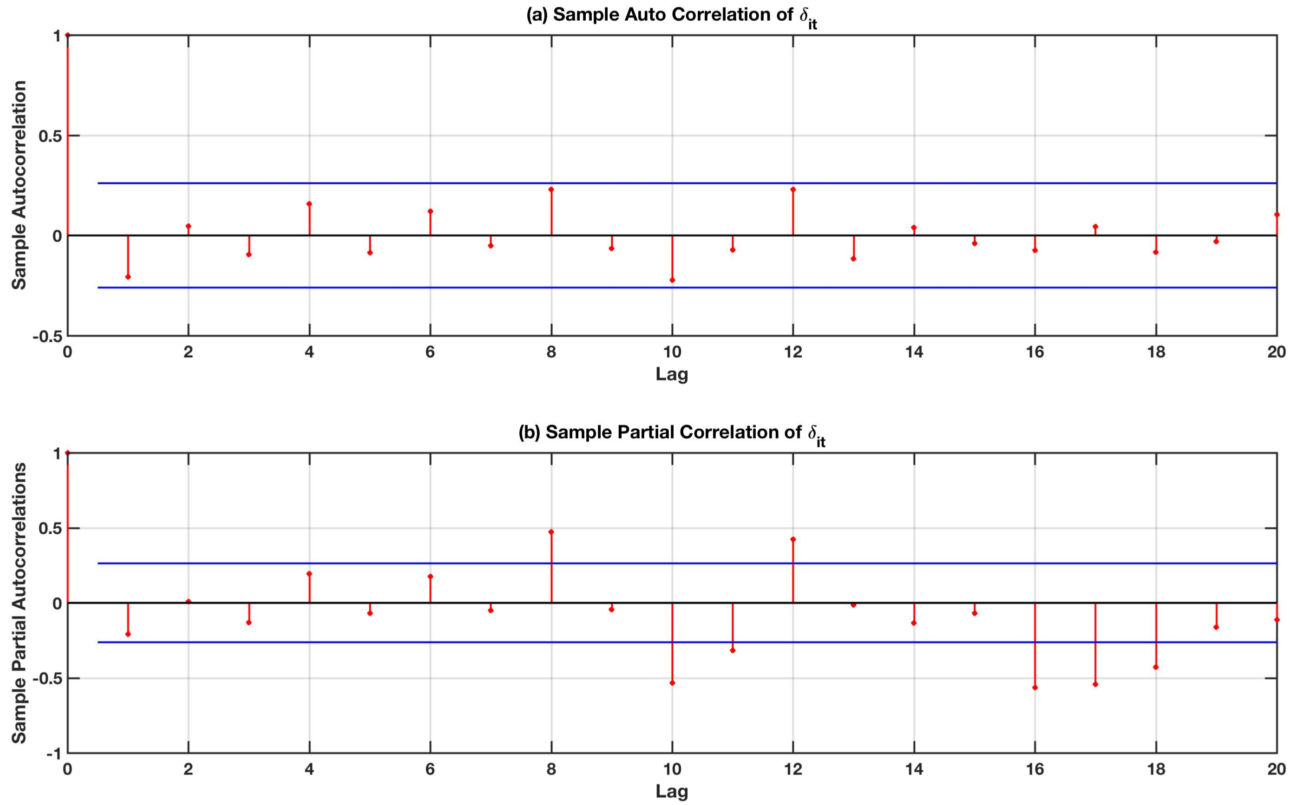
Notes: The y-axis indicates the prediction errors of the log inclusive value δ_{it}. The prediction error is calculated by the difference between δ_{it+1} and the period t prediction of this value using the realized δ_{it} and fitted $AR(1)$ model, for a consumer with draws in the 50 percentile for both random coefficients and κ_{it} at the upper bound.

Figure 8: Prediction Errors of ϕ_{it}



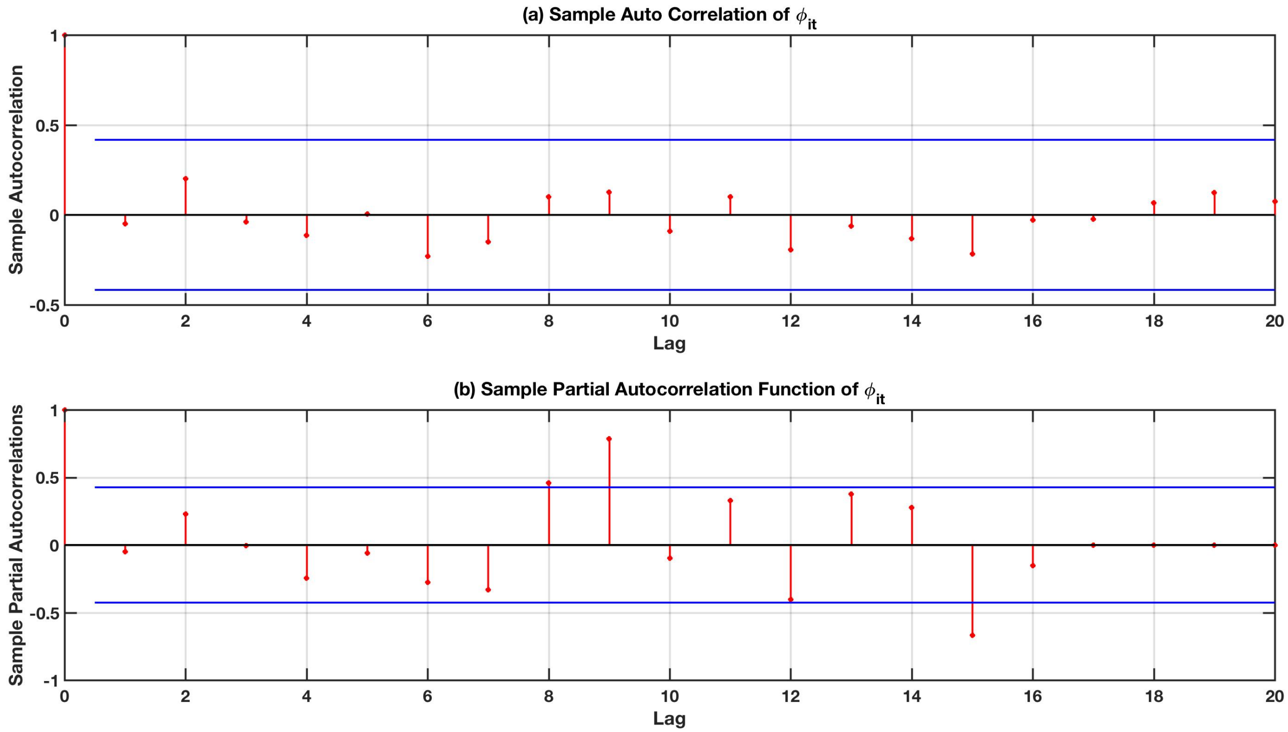
Notes: The y-axis indicates the prediction errors of the inclusive value ϕ_{it} . The prediction error is calculated by the difference between ϕ_{it+1} and the period t prediction of this value using the realized δ_{it}, ϕ_{it} and fitted $AR(1)$ model, for a consumer with draws in the 50 percentile for both random coefficients and κ_{it} at the upper bound.

Figure 9: Autocorrelation Test of Prediction Error of δ_{it}



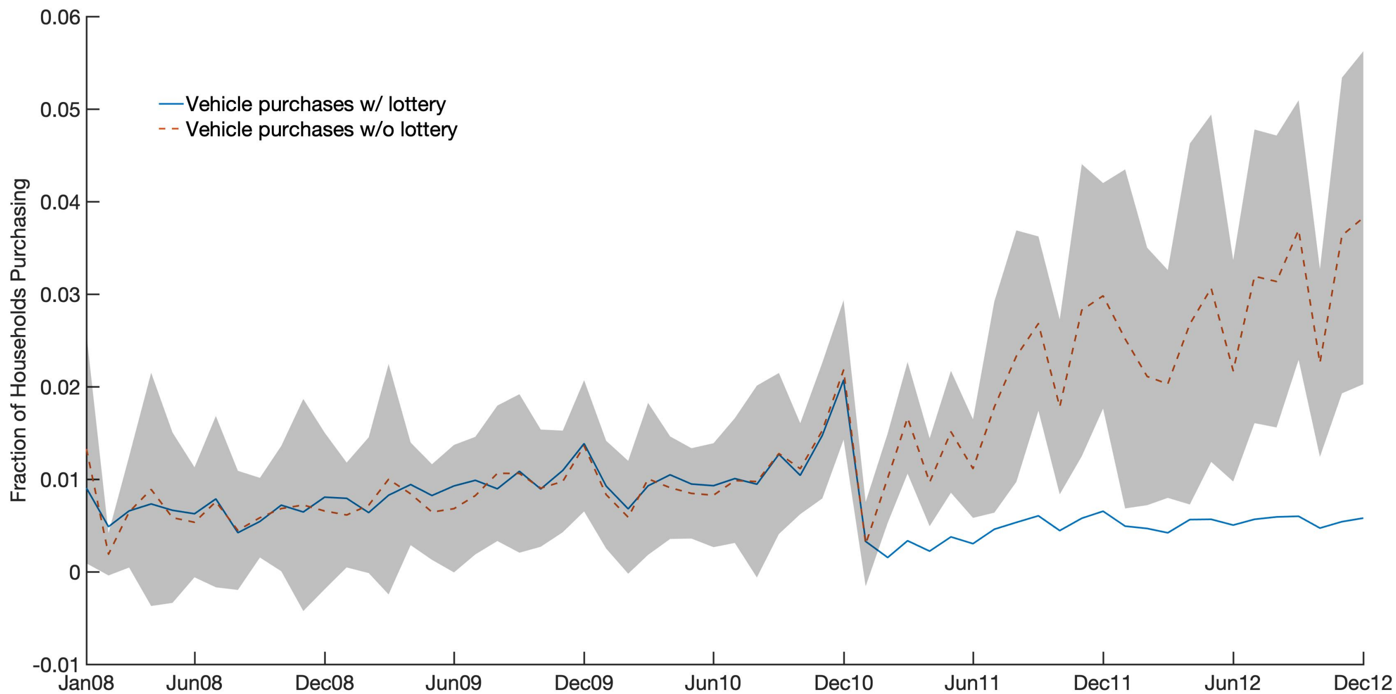
Notes: The y-axis in the top panel indicates the sample auto correlation of prediction error of $\delta_i t$ and the y-axis of the bottom panel indicates sample partial correlation of prediction error of δ_{it}. The confidence band is calculated by one unit of standard error, $1/\sqrt{T}$, where T equals to 59 months.

Figure 10: Autocorrelation Test of Prediction Error of ϕ_{it}



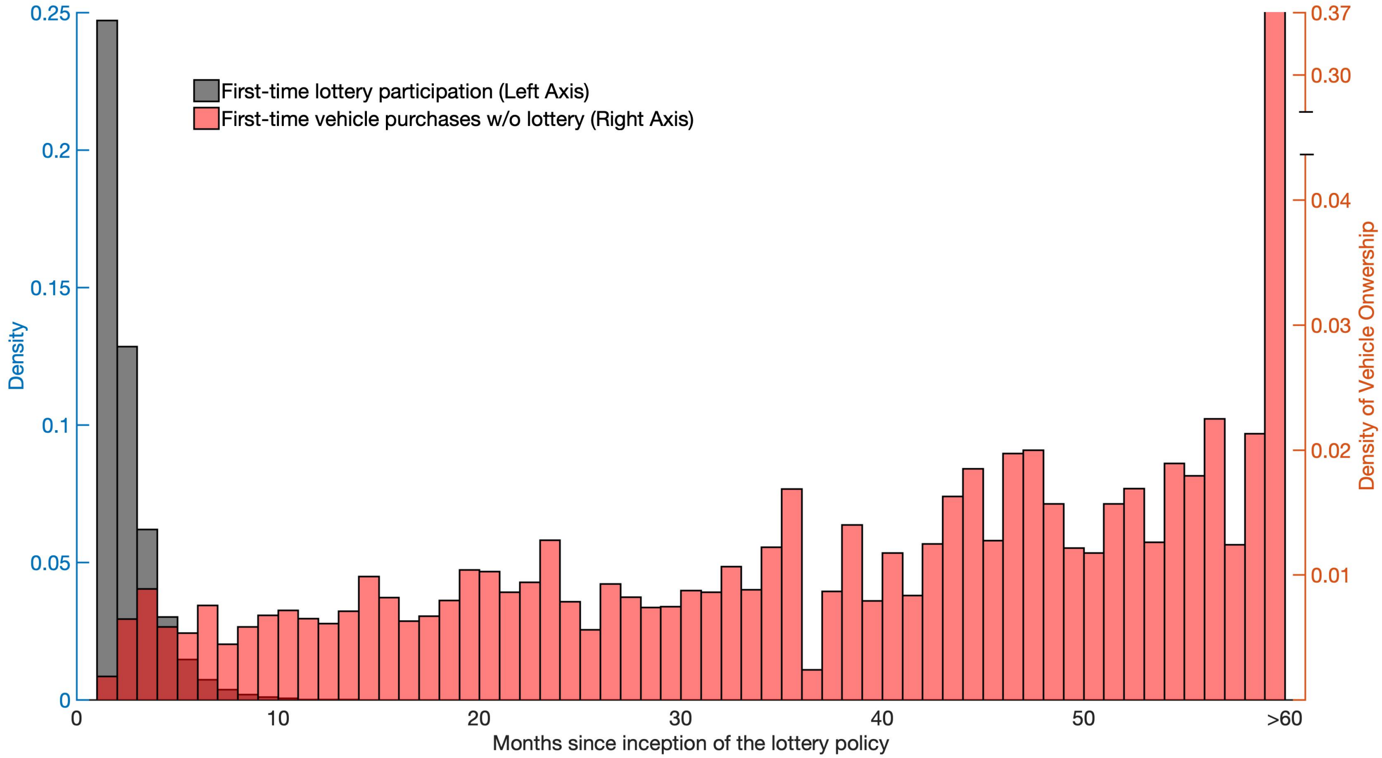
Notes: The y-axis in the top panel indicates the sample auto correlation of prediction error of $\phi_i t$ and the y-axis of the bottom panel indicates sample partial correlation of prediction error of ϕ_{it}. The confidence band is calculated by one unit of standard error, $1/\sqrt{T}$, where T equals to 23 months.

Figure 11: Sales Impact of the Lottery Policy



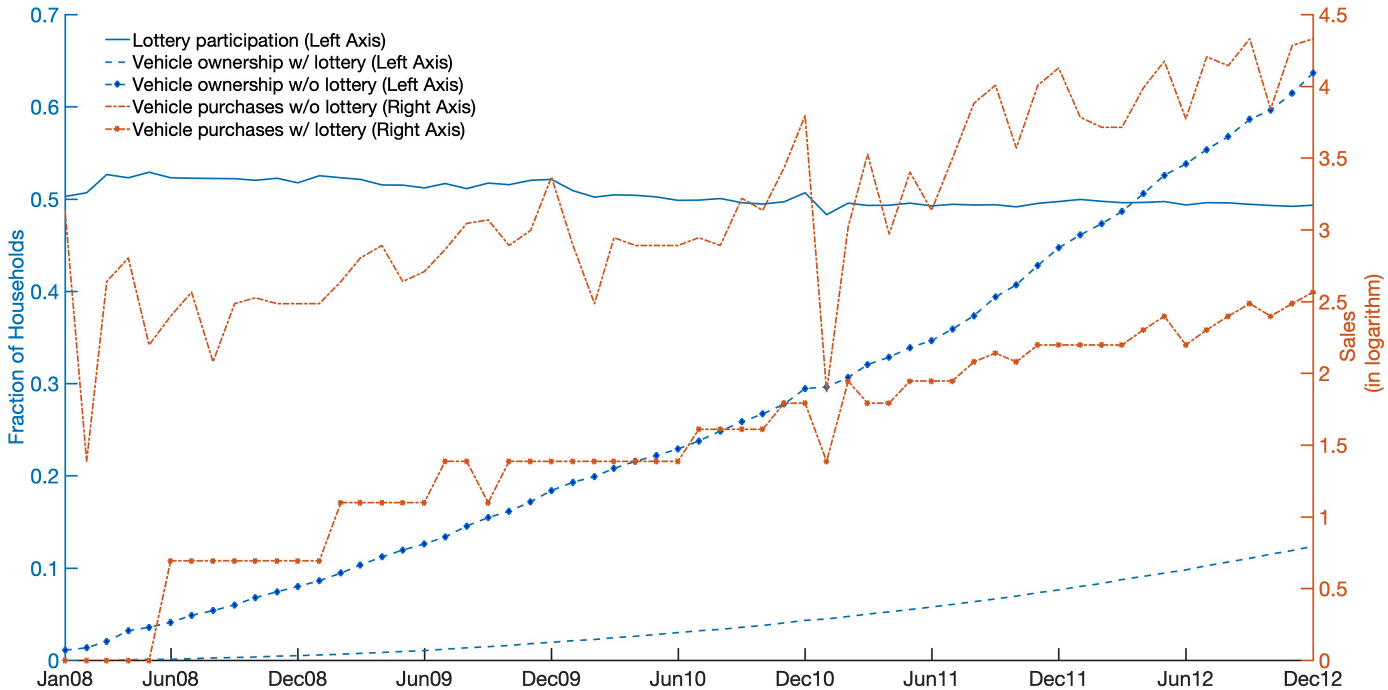
Notes: The y-axis indicates fraction of households purchasing a vehicle. The grey band is the 90% point-wise confidence interval from bootstrapping.

Figure 12: Households Timing Decisions



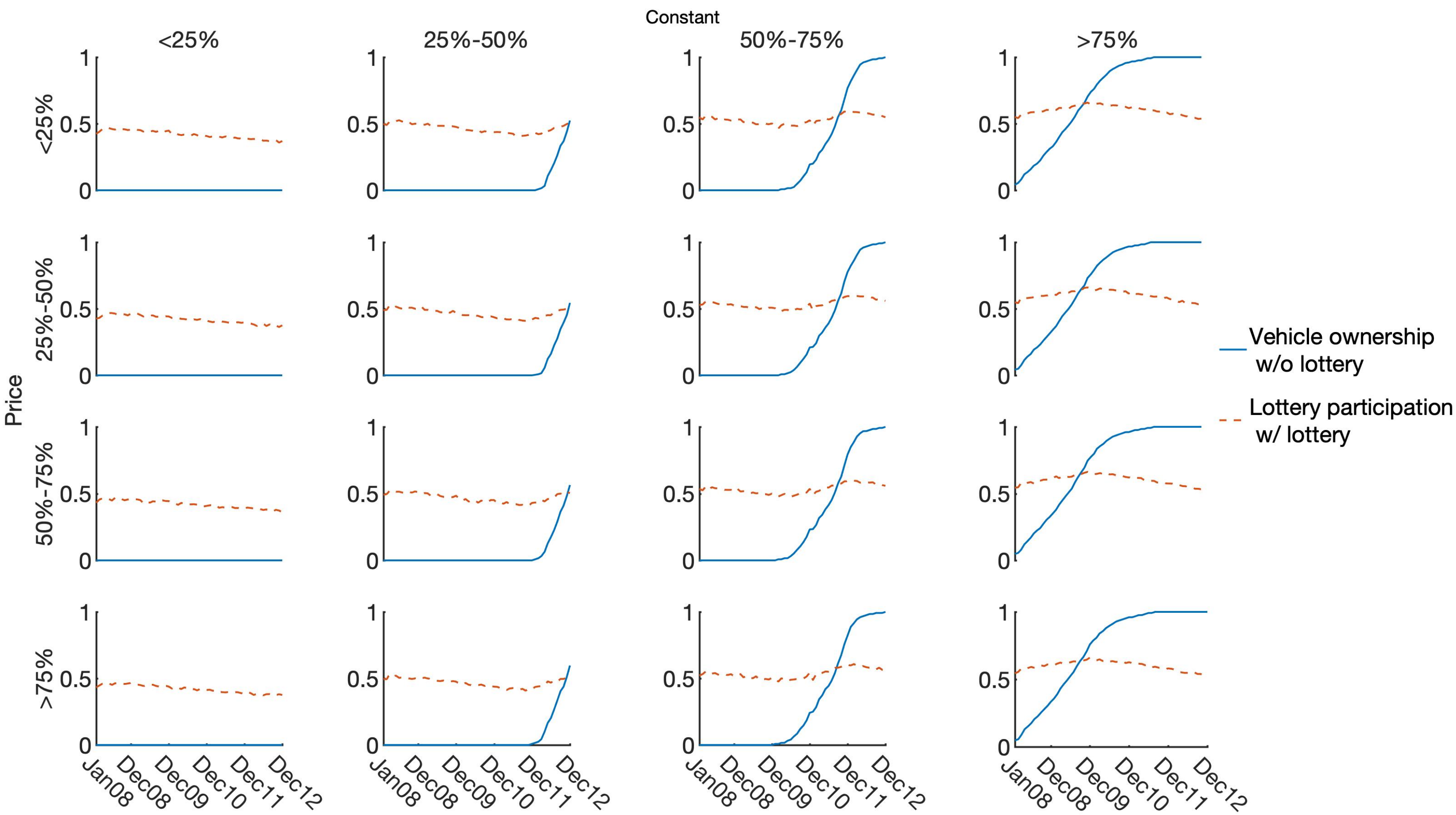
Notes: The x-axis indicates months before a household enters the lottery or start to own a vehicle.The y-axis indicates the fraction of total households that start to enter the lottery or own a vehicle in that month.

Figure 13: Counterfactual Simulation Results



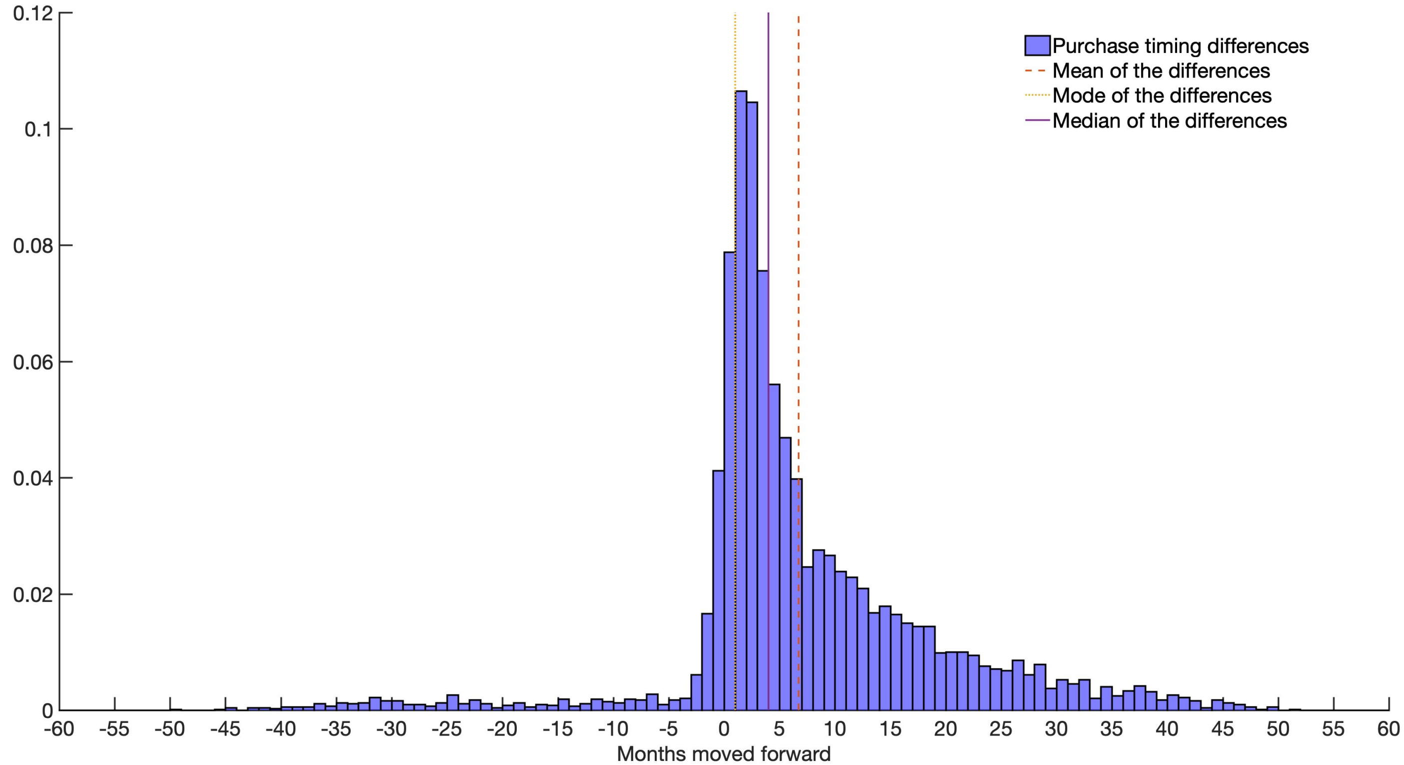
Notes: The y-axis on the left indicates the fraction of households being vehicle owners or lottery participants. The y-axis on the right indicates vehicle sales (in logarithm).

Figure 14: Counterfactual Results by Preferences



Notes: The y-axis indicates the fraction of households being vehicle owners or lottery participants. From top to bottom, the price coefficient increases. From left to right, the constant term (preference for ownership) increases.

Figure 15: Difference in Purchase Timing with and without the Policy



Notes: The y-axis indicates the fraction of lottery winners. The x-axis indicates difference between two points in time: the time when a household starts to own a vehicle in absence of quantity constraint, and the time when a household would purchase a vehicle for the first time under the lottery policy. A positive difference indicates early purchases induced by the policy.

Table 1: Summary Statistics

Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
	Model				Segement			
Price (in 1,000RMB)	311.29	277.83	36.49	1148.40	391.26	308.42	56.56	912.45
Monthly sales in Beijing	126	241	0	3464	7426	8355	103	62160
Monthly sales in Tianjin	57	126	0	2295	3381	3870	15	17435
Vehicle size (m2)	8.01	1.01	4.20	10.97	7.84	1.33	5.37	9.20
Displacement (liter)	2.11	0.85	0.90	6.20	2.35	1.09	1.04	4.32
Mini dummy	0.03	0.17	0.00	1.00	0.17	0.3732	0.00	1.00
Small dummy	0.21	0.41	0.00	1.00	0.17	0.3732	0.00	1.00
Medium dummy	0.35	0.48	0.00	1.00	0.17	0.3732	0.00	1.00
Upper Medium dummy	0.24	0.43	0.00	1.00	0.17	0.3732	0.00	1.00
Large dummy	0.14	0.35	0.00	1.00	0.17	0.3732	0.00	1.00
Luxury dummy	0.02	0.16	0.00	1.00	0.17	0.3732	0.00	1.00

Notes: The unit of observation on the left column is at the vehicle model-year-month level, and that on the right is at the segment-year-month level. Prices are in 1000s RMB at the 2012 price level and they include vehicle sales tax. The tax was at 10 percent in 2008, 2011 and 2012 but differed across vehicles with different engine size in 2009 and 2010 due to subsidies. There are 21,228 observations at the model-year-month level with 1,769 models (vintage-nameplate), and 360 observations at the segment-year-month level.

Table 2: The Policy Impacts from Reduced-form Analysis

	Specification 1		Specification 2	Specification 3	Specification 4
Variables	OLS	2SLS	2SLS	2SLS	2SLS
Ln(price)	-5.238	-7.815*	-11.350***	-6.786	-7.658*
	(4.005)	(4.719)	(3.893)	(4.570)	(4.516)
Beijing*2009	-0.033	-0.033			
	(0.052)	(0.052)			
Beijing*2010	0.021	0.021			
	(0.068)	(0.068)			
Beijing*2011			-0.946***	-3.475***	-3.541***
			(0.090)	(0.251)	(0.268)
Beijing*2012			-0.685***	-2.982***	-2.87***
			(0.126)	(0.312)	(0.321)
Beijing*2011*Ln(price)				0.478***	0.502***
				(0.047)	(0.050)
Beijing*2012*Ln(price)				0.440***	0.436***
				(0.057)	(0.059)
N	23616		42456	42456	40170

Notes: The dependent variable is ln(market shares). All specifications include model fixed effects, city-segment fixed effects and year-month fixed effects. Specification 1 uses the data from 2008 to 2010. Specifications 2 and 3 are based on full data from 2008 to 2012. Specification 4 uses the same observations as in Specifications 2 and 3 except dropping the observations in Nov. and Dec. of 2010 and Jan. of 2011 for Beijing to remove the anticipation effect. Instruments for price are constructed using the sales tax relief policy based on the engine size. Standard errors in parentheses are clustered at the model level.

Table 3: Parameter Estimates from GMM

Variables	Specification 1		Specification 2		Specification 3		Specification 4		Specification 5	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Utility of Vehicle (θ_{vc})										
Ln(Price) α_0^P	-13.45	0.50	-13.32	0.09	-13.20	0.13	-15.00	0.27	-13.60	2.65
Ln(Price)$\times$ Ln(Income) α_1^P	0.12	0.03	0.59	0.14	0.53	0.05	1.08	0.05	1.08	0.59
Ln(Income)	0.25	0.02	0.44	0.12	1.03	0.07	5.74	0.40	1.60	0.88
σ for Ln(Price)	0.24	0.11	0.51	0.14	0.50	0.02	0.02	0.01	0.16	0.09
σ for constant	4.14	0.23	3.69	0.10	3.95	0.12	1.37	0.17	1.56	0.07
Value of License										
γ	19.65	9.46	13.58	3.08	19.63	5.40	23.17	9.60	22.08	7.13
Persistent Demand Shock κ_{it}										
h	3.08	0.05	3.17	0.06	3.11	0.05	-	-	2.59	0.39
P	0.05	0.01	0.05	9.70×10^{-4}	0.04	3.33×10^{-3}	-	-	-	-
P_{inc1}	-	-	-	-	-	-	-	-	0.04	0.23
P_{inc2}	-	-	-	-	-	-	-	-	0.12	4.3×10^{-3}
P_{inc3}	-	-	-	-	-	-	-	-	0.08	0.19
P_{inc4}	-	-	-	-	-	-	-	-	0.08	0.67

Notes: Specification 1 is the benchmark and the preferred model. Specifications 1 and 2 use the full sample from 2008 to 2012. Specification 2 does not include the income moments for replacement buyers. Specification 3 drops the observations in Nov. and Dec. of 2010 and Jan. of 2011 for Beijing to remove the anticipation effect. Specification 4 assumes away the persistent demand shock to vehicle demand. Specification 5 allows transition probability of the persistent demand shock to vary across different income levels. The four income groups are corresponding to the income groups reported in Appendix Table 2a where inc_1 standards for the group of the lowest income level and inc_4 stands for the group of the highest income level.

Table 4: Sales Impact of Lottery Policy in Beijing (in thousand)

Year	Observed Sales	Variables	Counterfactual Sales		
			Benchmark	Alternative 1	Alternative 2
2011	327	Total	1,220 (585; 1,855)	1,136 (615; 1,657)	1,081 (545; 1,617)
		First-time (% to Total)	888 (72.77%)	835 (73.48%)	789 (72.97%)
2012	505	Total	1,810 (848; 2,772)	1,844 (903; 2,784)	1,814 (832; 2,795)
		First-time (% to Total)	1,071 (59.17%)	1,095 (59.38%)	1,064 (58.69%)

Notes: The benchmark model corresponds to the baseline specification in Table 3. Alternative 1 corresponds to the model that drops the observations in Nov. and Dec. of 2010 and Jan. of 2011 for Beijing to remove the anticipation effect. Alternative 2 corresponds to the model that allows transition probability of the persistent demand shock of demand to vary across different income levels. Total sales includes both first-time and replacement purchases. The 95% confidence intervals of total counterfactual sales are reported in the parenthesis.

Table 5a: Counterfactual Simulations from 2008 to 2012

Year	Scenario 1 Total Lottery Partcipants	Scenario 2 First-time Buyers
2008	50.58	0.59
2009	51.58	0.99
2010	49.77	0.64
2011	49.88	0.54
2012	49.07	2.74

Table 5b: Counterfactual Simulations in 2008

Date	Scenario 1 First-time Lottery Participants	Scenario 2 First-time Buyers
2008Q1	29.80	0.75
2008Q2	3.12	5.85
2008Q3	0.35	0.58
2008Q4	0.07	0.47

Notes: The first column in Table 5a indicates the total households that enter the lottery. The first column in Table 5b indicates total households that enter the lottery for the first time. The second column in Table 5a and 5b indicate the total households that buy a car for the first time. All numbers are in percentages and monthly averages. Scenario 1 represents the counterfactual environment that the lottery policy starts from the beginning of the sample period; scenario 2 represents the counterfactual environment that the lottery policy is absent from 2008 to 2012.

Table 6: Counterfactual Simulations

	2011	2012
Early Participation (% to total number of participation)	69.79	44.21
Months Moved Forward to Participate (Average over all early participants)	11.76	13.28
Advanced Purchases (% to total purchases)	43.09	24.81
Months Moved Forward to Purchase (Average over all early purchases)	3.72	1.41
Purchases Delayed (% to total ownership without policy)	67.57	38.50

Notes: Early Participation refers to households entering the lottery pool before they would purchase a vehicle in absence of the lottery policy. Early purchases refer to the purchases made by households before when they would purchase a vehicle in absence of the policy.

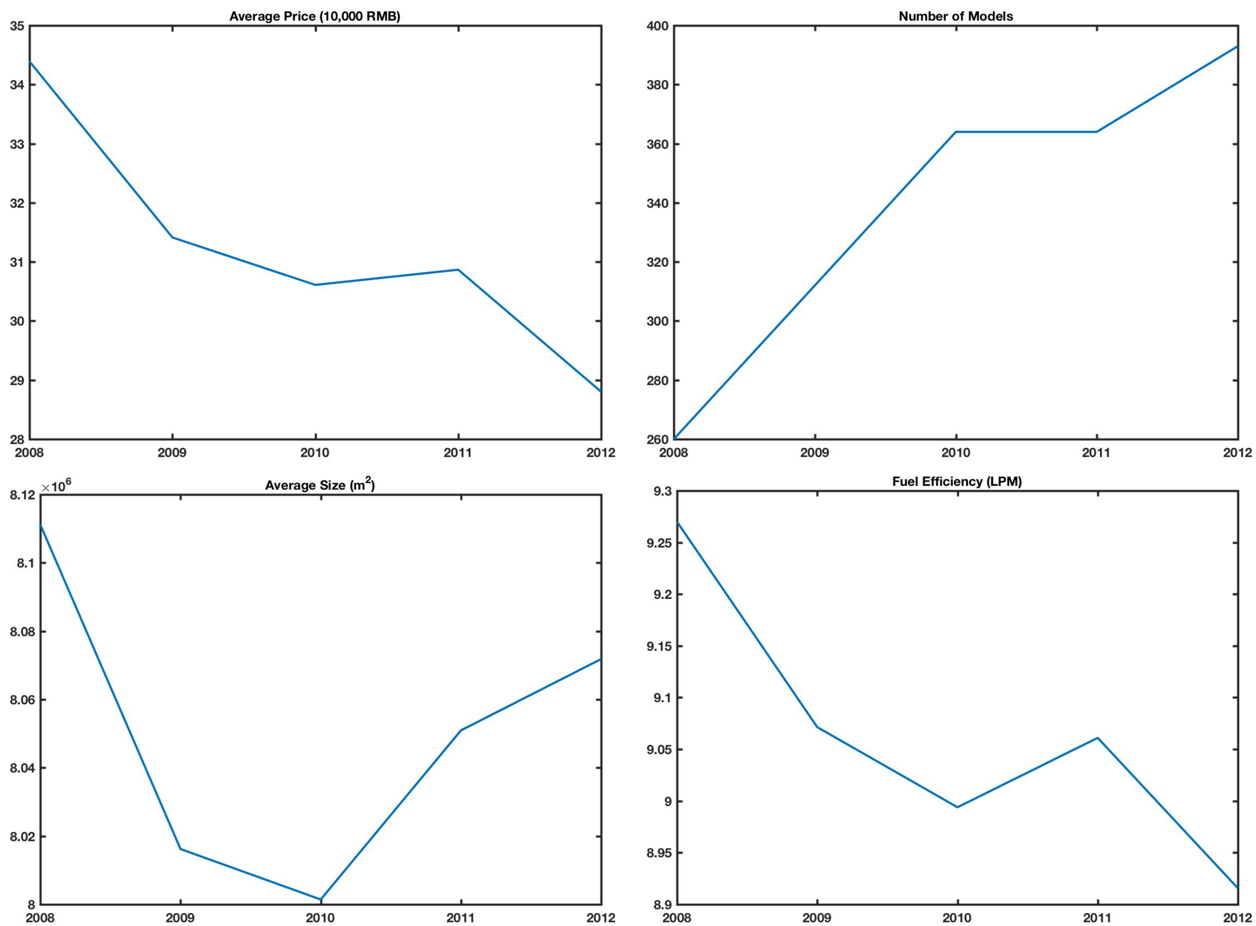
Table 7: Welfare Analysis

	Per Participant (1000 RMB)		Total (Billion RMB)
Total Consumer Welfare			
First Best	163.01		218.18
Second Best	121.98		163.26
(Percentage to First Best)		(74.83%)	
Lottery	77.30		103.46
(Percentage to First Best)		(47.42%)	
Welfare Loss			
Total Misallocation	85.71		114.72
Static Misallocation	41.03		54.92
(Percentage to total loss)		(47.87%)	
Early Participation	43.76		58.58
(Percentage to total loss)		(51.06%)	
Early Purchase	0.91		1.22
(Percentage to total loss)		(1.07%)	
Dynamic Inefficiency	44.68		59.80
(Percentage to total loss)		(52.13%)	

Notes: The first-best refers to the scenario where licenses are allocated to households with the highest valuation. The second-best refers to the scenario where licenses are allocated with a uniform probability among households who would purchase a vehicle in the current period in absence of the policy. Lottery refers to the current lottery policy where the decision horizon and the purchase timing are affected.

Appendices

Appendix Figure 1: Selected Vehicle Characteristics



Notes: Vehicle prices are computed based on the MSRP and sales tax. Average Sizes are computed by the product of vehicle length and width. Fuel efficiency is measure by liters of fuel per mile (LPM).

Table 1: Cities with Vehicle Quota Restrictions

Year	City	Annual Quota (2014 in thousand)	Implementation	Winning Probability
1990	Singapore	Sustainable Levels for road infrastructure development	Bi-monthly auction system to highest bidders	-
1994	Shanghai	100	Monthly Auction to highest bidders	-
2011	Beijing	130	Lottery	9.4 percent in January 2011; less than 0.1 percent by the end of 2017.
2011	Guiyang	50	Free lottery to enter the first ring zone	11.1 percent in the first lottery; 0.13 percent in December 2017.
2012	Guangzhou	108	Hybrid mechanism: 60,000 plates by lottery; 48,000 plates by auction.	4.48 percent in May 2013; 0.76 percent in December 2017.
2014	Tianjin	90	Hybrid mechanism: 50,000 plates by lottery; 40,000 plates by auction.	3 percent in the first lottery less than 0.1 percent by the end of2017.
2014	Hangzhou	80	Hybrid mechanism: 16,000 plates by lottery; 64,000 plates by auction.	2.2 percent in the first lottery; 0.85 percent in December 2017.
2015	Shenzhen	100	Hybrid mechanism: 50,000 plates by lottery; 50,000 plates by auction.	0.77 percent in the first lottery; 0.33 percent in December 2017.

Notes: Data and policy information are collected from Singapore Ministry of Transport, Beijing Municipal Commission of Transportation, Shanghai Municipal Commission of Transportation and EMBARQ of World Resources Institute.

Table 2a: The Share of Households by Income among Vehicle Buyers and All Households

City	Annnual Household Income (in Yuan)	New Vehicle Buyers					All Households				
		2008	2009	2010	2011	2012	2008	2009	2010	2011	2012
Beijing	<70K	12.64	12.81	15.28	9.78	6.54	65.47	51.62	44.87	38.32	33.41
Beijing	70K to 170K	43.68	66.56	59.26	58.70	52.34	31.60	45.19	50.88	55.83	58.05
Beijing	170K to 300K	26.44	12.50	16.67	26.09	28.97	2.61	2.70	3.67	4.81	7.07
Beijing	>300K	17.24	8.13	8.80	5.43	12.15	0.33	0.49	0.57	1.04	1.48
Tianjin	<70K	21.37	24.58	23.26	13.33	26.09	76.31	73.19	58.54	54.38	42.01
Tianjin	70K to 170K	56.41	57.54	55.04	63.81	63.04	22.64	25.44	39.72	42.97	54.72
Tianjin	170K to 300K	15.38	13.97	14.73	13.33	4.35	0.80	1.10	1.27	2.14	2.64
Tianjin	>300K	6.84	3.91	6.98	9.52	6.52	0.24	0.27	0.47	0.51	0.63

Table 2b: The Share of Households by Income among First Time Buyers and Replacement Buyers

City	Annnual Household Income (in Yuan)	First Time Buyers					Replacement Buyers				
		2008	2009	2010	2011	2012	2008	2009	2010	2011	2012
Beijing	<70K	13.41	13.06	15.98	11.69	5.88	0.00	10.34	9.09	0.00	9.10
Beijing	70K to 170K	42.68	67.70	62.37	61.04	54.12	60.00	55.17	31.82	46.67	45.46
Beijing	170K to 300K	26.22	11.68	14.43	22.08	24.71	30.00	20.69	36.36	46.67	45.46
Beijing	>300K	17.68	7.56	7.22	5.19	15.29	10.00	13.79	22.73	6.67	0.00
Tianjin	<70K	21.70	22.56	21.05	13.48	31.58	18.18	46.67	40.00	12.50	0.00
Tianjin	70K to 170K	58.49	59.76	55.26	64.04	60.53	36.36	33.33	53.33	62.50	75.00
Tianjin	170K to 300K	14.15	14.63	16.67	14.61	5.26	27.27	6.67	0.00	6.25	0.00
Tianjin	>300K	5.66	3.05	7.02	7.87	2.63	18.18	13.33	6.67	18.75	25.00

Notes: New Vehicle Buyers include both first time buyers and replacement buyers. The income data for vehicle buyers comes from household survey data conducted by the National Information Center. The data on all households are from Annual Statistical Yearbook for each city by Bureau of Statistics.

Table 3: City Characteristics in Beijing and Tianjin

Year	City	No. of Households (mil.)	Average Household Income (in Yuan)	New Vehicle Sales	National Vehicle Sales(mil.)	% in nation
2008	Beijing	605.99	69,230	419,703	6.60	6.21
2009	Beijing	636.29	74,866	610,076	10.33	5.91
2010	Beijing	668.10	81,404	815,211	13.76	5.93
2011	Beijing	687.86	88,838	346,207	14.47	2.39
2012	Beijing	704.89	98,466	536,216	15.50	3.46
2008	Tianjin	347.88	56,131	160,221	6.76	2.37
2009	Tianjin	356.92	61,737	223,774	10.33	2.17
2010	Tianjin	366.20	69,477	276,716	13.76	2.01
2011	Tianjin	383.35	76,455	278,336	14.47	1.92
2012	Tianjin	399.92	84,138	292,442	15.50	1.89

Notes: The sales data are from R.L. Polk & CO. and other variables are from various issues of Annual Social and Economic Development Report by each of the cities. The average income is nominal. New vehicle sales include passenger cars and ligth truck.