Modeling Supply and Demand in the Chinese Automobile Industry[1]

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1. Introduction

China is experiencing rapid economic growth and, along with it, rapid growth in vehicle ownership. Evidence from Chinese cities suggests average annual growth rates in per capita vehicle ownership of 10% to 25% (Darido, Torres, and Mehndiratta, 2014). According to data from the China Statistical Yearbook, vehicle ownership increased by nearly 56 times between 1990 and 2011. The rapid growth in vehicle ownership and vehicle usage is linked to increasing global warming, emissions, air pollution, and other problems.

For our research, we are developing and estimating a structural econometric model to estimate demand and cost parameters for all vehicles in China. We are applying our model to annual data we have collected on sales, prices, and characteristics of the majority of vehicle makes and models in China, including electric vehicles, hybrid vehicles, and alternative-fueled vehicles, over the period 2004 to 2013. In addition to price, we have collected data on vehicle characteristics, such as power, fuel efficiency, vehicle type (e.g., sedans, SUVs, pick-ups, etc.), and displacement for the majority of vehicle makes and models in China. Our model will enable us to estimate demand- and cost-side parameters, own- and cross-price elasticities, markups, and variable profits for alternative vehicles.

The parameters we are estimating will enable us to better understand what factors affect the demand and cost of vehicles in China, and how consumers in China trade off various vehicle characteristics (such as fuel efficiency, whether the vehicle is an electric vehicle, etc.) with each other and with price. We will use the model to simulate the demand and cost for new vehicles, and also the effects of various government policies on demand and cost.

Our structural econometric model has several advantages over a survey approach. First, econometric models are estimated using actual data on actual vehicle purchase decisions, and therefore may be more accurate a depiction of consumer preferences, since these preferences are revealed by the actual decisions they make. In contrast, surveys are based on self-reported responses to questions and may be subject to many errors and biases that cause these responses to be inaccurate representations of the truth.

A second advantage of our econometric approach over a survey approach is that we will estimate our econometric models using a comprehensive data set we have collected and constructed on sales, prices, and characteristics of the majority of vehicle makes and models in China, and will therefore base our models and analysis on the vehicle purchase decisions of all vehicle owners in China, not just those of the consumers that are surveyed. Our comprehensive data set not only provides more information, but also is not subject to sample selection issues that would plague a survey of a sample of the population.

A third advantage of our econometric approach over a survey approach is that our econometric model will enable us to statistically control for multiple factors that may affect vehicle purchase decisions, including price; vehicle characteristics such as fuel economy, horsepower, and size; and consumer characteristics in a quantitative and rigorous manner.

A fourth advantage of the structural model is that the parameters we are estimating enable us to calculate consumer utility, firm profits, and welfare.

A fifth advantage of our structural econometric approach is that it enables us to estimate standard errors and confidence intervals for our parameters, and therefore to ascertain whether our parameters are statistically significant.

A sixth advantage of our structural econometric approach is that we can use the estimated parameters to simulate demand, supply, and welfare under counterfactual policy scenarios.

These counterfactual policy simulations will enable us to analyze the effects of vehicle-related policies in China, including those regarding alternative vehicles.

Our research builds on the work of Berry, Levinsohn and Pakes (1995), who develop a model for empirically analyzing demand and supply in differentiated products markets and then apply these techniques to analyze the equilibrium in the U.S. automobile industry. Their framework enables one to obtain estimates of demand and cost parameters for a class of oligopolistic differentiated products markets. Unlike traditional logit demand models, their random coefficients model allows for interactions between consumer and product characteristics, thus generating reasonable substitution patterns. Estimates from their framework can be obtained using only widely available product-level and aggregate consumer-level data, and they are consistent with a structural model of equilibrium in an oligopolistic industry. They apply their techniques to the U.S. automobile market, and obtain cost and demand parameters for (essentially) all models marketed over a twenty year period. On the cost side, they estimate cost as a function of product characteristics. On the demand side, they estimate own- and cross-price elasticities as well as elasticities of demand with respect to vehicle attributes (such as weight or fuel efficiency).

Our research innovates upon the Berry et al. (1995) work by developing a model of the Chinese automobile market; by including alternative vehicles so that in addition to cost and demand parameters relating to gasoline-fueled vehicles, cost and demand parameters relating to alternative vehicles can be estimated; and by modeling the behavior of not only private automobile companies but also the state-owned automobile companies in China.

Our research is significant for industry, government, society, academia, and NGOs. Our model of the demand and cost in the Chinese automobile market will be significant for industry, particularly car manufacturers interested in better targeting cars, including alternative vehicles, for the Chinese market. Our estimates of the factors that affect demand and supply in the Chinese automobile market is significant for policy-makers interested in developing incentive policies to increase market penetration of alternative vehicles with potential environmental and climate benefits.

2. Background

In 2009, China's automobile market became the largest in the world, surpassing the U.S. automobile market both in sales and production. The annual gross product of the automobile industry has exceeded 5% of the annual GDP every year since 2002, and was as high as 7.4% of GDP in 2010.[2] The Chinese automobile industry underwent several phases of growth since the start of economic reform in 1978. At that time, automobile manufacturing was very low in productivity. In the year 1980, total vehicle output was around five thousand only. As income grew, households' demand for passenger vehicle grew rapidly, which resulted in a large amount of imports. In order to protect the vulnerable and immature industry, tariffs were set as high as 250% (Li, Xiao and Liu, 2015).

Several large state-owned automobile enterprises tried to partner with foreign auto manufacturers to form joint ventures to increase capacity and enhance technical capabilities. However, foreign ownership was capped at 50% to protect domestic producers. In 1994, China's National Development and Reform Commission (NDRC) initiated an automobile industry policy encouraging state-owned firms to partner with international car makers to form joint ventures (Li, Xiao and Liu, 2015).

[2] These statistics were calculated using GDP data from the National Bureau of Statistics of China and automobile industry gross product data from Chinese Automobile Industry Yearbook.

Following this policy, more joint ventures were formed between large state-owned automobile companies and foreign auto manufacturers (Li, Xiao and Liu, 2015). Meanwhile, local and private producer also entered the market.

In 2001, China entered the WTO. In order to fulfill its commitment, the government gradually cut the tariffs on automobiles from 100% to 25% during 5-year transitional period. However, the market shares of imports further dropped from about 6% in 2001 to 3% in 2006 and it has stayed at that level since then (Li, Xiao and Liu 2015).

The Chinese manufacturers of passenger vehicles can be categorized into two different types: indigenous-brand manufacturers, such as BYD, Geely, and Chery; and joint ventures between domestic manufacturers and foreign manufacturers, such as Shanghai Automotive Investment Company (BAIC) with Hyndai, and Dongfeng with Honda. Figure 1, adapted from (Hu, Xiao, and Zhou 2014), presents the market structure of the Chinese automobile industry. Those car makers in large boxes are the top state-owned automobile groups in China. The ones in small isolated boxes at the bottom are indigenous local makers. On one hand, a single auto group might partner with multiple foreign car manufactures. For example, Shanghai Auto has cooperated with General Motors, and Volkswagen. Dofeng Motors partner with Nissan, Kia and PSA. On the other hand, a foreign car manufacture is also possible to cooperate with several local car manufacturers. Take Honda as example, it partners with both Donfeng Group and Guangdong Auto. Toyota, as another Japanese automaker, cooperates with both Fist Auto Work and Guangdo Auto. Besides large stated-owned auto groups, private car makers also partner with foreign makers. Huachen Auto cooperates with BMW. Those joint ventures account for two thirds of the passenger vehicle market with the rest mostly taken up by indigenous brands (Li, Xiao and Liu, 2015).

Figure 2 presents the location of the automobile firms listed in Figure 1. Most of the automakers are located along the east of the continent. Two of the “China Automobile Group Four” are located on the east, with First Auto Work on the northeast, Shanghai Automotive Investment Company (SAIC) on the Southeast. The other two Dongfeng Group is in the middle east while Chang’an Automobile Group is in central China. Two large indigenous firms Geely and Chery are on the southeast part of China.

In 2005, CAAM, which is the designated statistic organization of automobile industry that categorizes vehicles, reclassified vehicles into two broad categories: passenger vehicles and commercial vehicles. Passenger vehicle can be further divided into four categories: Basic Passenger Vehicle (BPV), Sports Utility Vehicle (SUV), Multi-purpose Vehicle (MPV) and others (such as crossovers). In 2012, according to the China Automobile Industry Year Book, the total BPV output is 10.767 million and that for MPV and SUV is 491.896 thousand and 1.999 million respectively. The total output and sales for passenger vehicle is 13.258 million and 13.239 million.

According to China’s National Bureau of Statistics, from 2004 to 2014, the total number of civil passenger vehicle owned in China has increased from 17.35 million to 123.27 million, with an annual growth rate of 21.69%. Including the total civil trucks, the total number of civil vehicle owned in China was 145.98 million in 2014.

In the year 2010, the Chinese government established a project called “energy saving projects”, using fiscal subsidy to encourage energy saving. Some autos with small displacement (less than 1.6L) will receive a subsidy (directly to the car makers) such that the market price is the price after subsidized.[3]

3. Literature Review

The first strand of literature we build upon is that on structural econometric models of demand and supply in differentiated products markets. Under the assumption that demand can be described by a discrete choice model and that prices are endogenously determined by price-setting firms, Berry (1994) develops techniques which, in contrast to some previous empirical work, explicitly allow for the possibility that prices are correlated with unobserved demand factors in the cross section of markets. The estimation is proposed by "inverting" the market share equation to find the implied mean levels of utility for each good. The method allows for estimation by traditional instrumental variables techniques.

Goldberg (1995) develops and estimates a model of the U.S. Automobile Industry. On the demand side, a discrete choice model is estimated using micro data from the Consumer Expenditure Survey. The estimation results are used in conjunction with population weights to derive aggregate demand. On the supply side, the automobile industry is modelled as an oligopoly with differentiation. Equilibrium is characterized by the first-order conditions of the profit maximizing firms. The estimation results are used in counterfactual simulations to investigate two trade policy issues: the effects of the voluntary export restraint, and exchange rate pass-through.

Berry, Levinsohn and Pakes (1995) develop techniques for empirically analyzing demand and supply in differentiated products markets and then apply these techniques to analyze the

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equilibrium in the U.S. automobile industry. The framework they present enables one to obtain estimates of demand and cost parameters for a class of oligopolistic differentiated products markets, using only widely available product-level and aggregate consumer-level data, which are consistent with a structural model of equilibrium in an oligopolistic industry.

Feenstra and Levinsohn (1995) demonstrate how to estimate a model of oligopoly pricing when products are multi-dimensionally differentiated. They provide an empirical counterpart to recent theoretical work on product differentiation. Using specifications informed by economic theory, they estimate price-cost margins for products differentiated in many dimensions.

Petrin (2002) develops a technique useful for obtaining more precise estimates of demand and supply curves when constrained to market-level data. The technique augments the estimation routine with data on the average characteristics of consumers that purchase different products. He applies his technique to the automobile market, estimating the economic effects of the minivan introduction. He shows that the results obtained are meaningfully different from those yielded by the standard approaches. Benefits accruing to both minivan and non-minivan consumers are reported.

Berry, Levinsohn and Pakes (2004) show how rich sources of information on consumer choice can help to identify demand parameters in a widely used class of differentiated products demand models. In particular, they show how to use "second-choice" data on automotive purchases to obtain good estimates of substitution patterns in the automobile industry. They use their parameter estimates to make out-of-sample predictions about important recent changes in industry structure.

Hoderlein, Klemela and Mammen (2008) consider the case in which the coefficients in the relationship between a dependent variable and a set of regressors are random and distributed independently from the regressors. Their aim is to identify and estimate the distribution of the coefficients non-parametrically. They propose a kernel based estimator for the joint probability density of the coefficients. Although this estimator shares certain features with standard non-parametric kernel density estimators, it also differs in some important characteristics which are due to the very different set up they are considering. Most importantly, the kernel is nonstandard, and derives from the theory of Radon transforms. Consequently, they call their estimator the Radon Transform Estimator (RTE). They establish the large sample behavior of this estimator, in particular rate optimality and asymptotic distribution. In addition, they extend the basic model to cover extensions including endogenous regressors and additional controls. Finally, they analyze the properties of the estimator in finite samples by a simulation study, as well as an application to consumer demand using British household data.

Dube, Fox and Su (2012) derive numerical theory results characterizing the properties of the nested fixed point algorithm used to evaluate the objective function of the Berry, Levinsohn and Pakes (1995) estimator. They recast the estimation as a mathematical program with equilibrium constraints, which can be faster and which avoids the numerical issues associated with nested inner loops. They use several Monte Carlo and real-data experiments to support that the constrained optimization approach has advantages both for forward-looking demand models where the Bellman equation must also be solved repeatedly and for static Berry, Levinsohn and Pakes (1995) models for large-dimensional problems with many markets.

Knittel and Metaxoglou (2014) document the numerical challenges they experienced estimating random coefficients demand models as in Berry et al. (1995) using two well-known data sets and a thorough optimization design. The optimization algorithms often converge at points where the first and second order optimality conditions fail. There are also cases of convergence at local optima. On convergence, the variation in the values of the parameter estimates translates into variation in the models' economic predictions.

Reynaert and Verboven (2014) shed light on the performance of Berry, Levinsohn and Pakes' (1995) GMM estimator of the aggregate random coefficient logit model. Based on an extensive Monte Carlo study, they show that the use of Chamberlain's (1987) optimal instruments overcomes many problems that have recently been documented with standard, non-optimal instruments. Optimal instruments reduce small sample bias, but they prove even more powerful in increasing the estimator's efficiency and stability. They consider a wide variety of data-generating processes and an empirical application to the automobile market. They also consider the gain of other recent methodological advances when combined with optimal instruments.

Berry and Haile (2014) present new identification results for nonparametric models of differentiated products markets, using only market level observables. They specify a nonparametric random utility discrete choice model of demand allowing rich preference heterogeneity, product/market unobservables, and endogenous prices. Their supply model posits nonparametric cost functions, allows latent cost shocks, and nests a range of standard oligopoly models. Two complementary approaches are explored. The first demonstrates identification under the same nonparametric instrumental variables conditions required for identification of regression models. The second treats demand and supply in a system of nonparametric simultaneous equations, leading to constructive proofs exploiting exogenous variation in demand shifters and cost shifters. They also derive testable restrictions that provide the first general formalization of Bresnahan's (1982) intuition for empirically distinguishing between alternative models of oligopoly competitions.

Berry and Haile (2015) review some recent work studying identification in a broad class of empirical models of demand for and supply of differentiated products. They show that parametric functional forms and distributional assumptions are not essential for identification. Rather, identification relies primarily on the standard requirement that instruments be available for the endogenous variables, typically prices and quantities. They discuss the kinds of instruments needed for identification and how the reliance on instruments can be reduced by nonparametric functional form restrictions or better data.

Bajari et al. (2015) propose a method of combining the underlying models via linear regression to improve out-of-sample prediction accuracy and obtain parametric rates of convergence. The method they use has several appealing features such as: robust to a large number of potentially-collinear repressors; easily scaled to very large data sets. The method is illustrated by using a standard scanner panel data set to estimate promotional lift and they find that the estimates are considerably more accurate in out of sample predictions of demand than some commonly used alternatives.

The second strand of literature we build upon is that on vehicle markets and policy, particularly for alternative vehicles. Gallagher and Muehlegger (2011) study the relative efficacy of state sales tax waivers, income tax credits, and non-tax incentives to induce consumer adoption of hybrid-electric vehicles. They find that the type of tax incentive offered is as important as the generosity of the incentive. Additionally, they examine how adoption varies with fuel prices. By comparing consumer response to sales tax waivers and estimated future fuel savings, they estimate an implicit discount rate of 14.6% on future fuel savings.

Beresteanu and Li (2011) analyze the determinants of hybrid vehicle demand, focusing on gasoline prices and income tax incentives. They find that hybrid vehicle sales in 2006 would have been 37% lower had gasoline prices stayed at the 1999 levels, and the effect of the federal income tax credit program is estimated at 20% in 2006. Under the program, the cost of reducing gasoline consumption was $75 per barrel in government revenue and that of CO_2 emission reduction was $177 per ton. They show that the cost effectiveness of federal tax programs can be improved by a flat rebate scheme.

Sallee (2011) estimates the incidence of tax incentives for the Toyota Prius. Transaction microdata indicate that both federal and state incentives were fully captured by consumers. This is surprising because Toyota faced a binding production constraint, which suggests that they could have appropriated the gains. The paper proffers an explanation based on an intertemporal link in pricing that stems from search frictions, which has the unconventional implication that statutory burden influenced economic burden.

Sallee and Slemrod (2012) analyze notches in fuel economy policies, which aim to reduce negative externalities associated with fuel consumption. They provide evidence that automakers respond to notches in the Gas Guzzler Tax and mandatory fuel economy labels by precisely manipulating fuel economy ratings so as to just qualify for more favorable treatment. They then describe the welfare consequences of this behavior and derive a welfare summary statistic applicable to many contexts. In brief, notches are an inefficient substitute for smooth policies because they create marginal incentives that vary among decision makers and induce some individual actions that have negative net social benefits.

Jacobsen (2013) employs an empirically estimated model to study the equilibrium effects of an increase in the US corporate average fuel economy (CAFE) standards. He identifies and models heterogeneity across firms and finds that the profit impacts of CAFE fall almost entirely on domestic producers. The welfare analyses consider the simultaneous household decision of vehicle and miles traveled, allowing direct comparison with a gasoline tax. Finally, he considers dynamic impacts in the used car market and finds these comprise nearly half the gross welfare cost of CAFE and fall disproportionately on low-income households. Contrary to previous results, the overall welfare costs are regressive.

Heutel and Muehlegger (2015) study the effect of differences in product quality on new technology diffusion. They propose a model in which heterogeneity in perceived product quality affects consumer adoption. If consumers experientially infer the quality of a technology, an increase in initial exposure to a low-quality product may inhibit subsequent diffusion. Incentives intended to speed up adoption may in fact have the opposite effect, if they propagate low-quality signals. They examine the predictions of the model using sales data for 11 hybrid-vehicle models between 2000 and 2006. They find that conditional on overall hybrid vehicle adoption in the first 2 years, locations with a relatively high Prius market share experienced faster subsequent adoption than states with a relatively high Insight market share.

Jacobsen and van Benthem (2015) estimate the sensitivity of scrap decisions to changes in used car values and show how this “scrap elasticity” produces emissions leakage under fuel efficiency stands, a process known as the Gruenspecht effect. After first estimating the effect of gasoline prices on used vehicle values and scrappage of vehicles with different fuel economies, they then estimate the scrap elasticity itself, which they found to be -0.7. When applied in a model of fuel economy standards, 13-16 percent of the expected fuel savings leak away through the used vehicle market, which effect rivals or exceeds the importance of the often-cited mileage rebound effect.

Li and Zhou (2015) examine the dynamics of technology adoption and critical mass in network industries with an application to the U.S. electric vehicle (EVs) market, which exhibits indirect network effects in that consumer EV adoption and investor deployment of public charging stations are interdependent. Using a data set of quarterly EV sales in 354 U.S. metro areas from 2011 to 2013, they quantify indirect network effects and simulate long-run market outcomes in each of the Metropolitan Statistical Areas (MSAs). Their analysis provides robust and significant evidence of indirect network effects in this market. Also their simulations show several different market equilibrium outcomes across the MSAs in the long run with a significant number of them exhibiting multiple equilibria and critical mass.

Aghion et al. (2016) construct new firm-level panel data on auto industry innovation distinguishing between "dirty" (internal combustion engine) and "clean" (e.g., electric, hybrid, and hydrogen) patents across 80 countries over several decades. They show that firms tend to innovate more in clear (and less in dirty) technologies when they face higher tax-inclusive fuel prices. Furthermore, there is path dependence in the type of innovation (clean/dirty) both from aggregate spillovers and from the firm's own innovation history.

Sallee, West and Fan (forthcoming) measure consumers' willingness to pay for fuel economy using a novel identification strategy and high quality microdata from wholesale used car auctions. They leverage differences in future fuel costs across otherwise identical vehicles that have different current mileage, and therefore different remaining lifetimes. By seeing how price differences across high and low mileage vehicles of different fuel economies change in response to shocks to the price of gasoline, they estimate the relationship between vehicle prices and future fuel costs. Their data suggest that used automobile prices move one for one with changes in present discounted future fuel costs, which implies that consumers fully value fuel economy.

Anderson and Sallee (forthcoming) present a simplified model of car choice that allows them to emphasize the relationships between fuel economy, other car attributes, and miles traveled. They focus on greenhouse gas emissions. Besides the main familiar conclusion that standards are substantially less efficient than a fuel tax, they make the points about the relative importance of rebound effect, on the effects of attribute-based policies, and the implications of behavioral biases.

The third strand of literature we build upon is that on vehicle markets and policy in China. Huo et al. (2007) develop a methodology to project growth trends of the motor vehicle population and associated oil demand and carbon dioxide emissions in China through 2050. In particular, the numbers of highway vehicles, motorcycles, and rural vehicles are projected under three scenarios of vehicle growth by following different patterns of motor vehicle growth in Europe and Asia. Projections show that by 2030 China could have more highway vehicles than the United States has today.

China's vehicle population is widely forecasted to grow 6-11% per year into the foreseeable future. Barring aggressive policy intervention or a collapse of the Chinese economy, Wang, Teter and Sperling (2011) suggest that those forecasts are conservative. They analyze the historical vehicle growth patterns of seven of the largest vehicle producing countries at comparable times in their motorization history. They estimate vehicle growth rates for this analogous group of countries to have 13-17% per year- roughly twice the rate forecasted for China by others. Applying these higher growth rates to China results in the total vehicle fleet reaching considerably higher volumes than forecasted by others, implying far higher global oil use and carbon emissions than projected by the International Energy Agency and others.

Lin and Zeng (2013) estimate the price and income elasticities of demand for gasoline in China. Their estimates of the intermediate-run price elasticity of gasoline demand range between -0.497 and -0.196, and their estimates of the intermediate-run income elasticity of gasoline demand range between 1.01 and 1.05. They also extend previous studies to estimate the vehicle miles traveled (VMT) elasticity and obtain a range from -0.882 to -0.579.

Lin and Zeng (2014) calculate the optimal gasoline tax for China using a model developed by Parry and Small. They calculate the optimal adjusted Pigovian tax in China to be $1.58 /gallon which is 2.65 times more than the current level. Of the externalities incorporated in this Pigovian tax, the congestion costs are taxed the most heavily, at $0.82/gallon, followed by local air pollution, accident externalities, and finally global climate change.

Hu, Xiao and Zhou (2014) apply a non-nested hypothesis test methodology to data on Chinese passenger vehicles to identify whether price collusion exists within corporate groups or across groups. Their empirical results support the assumption of Bertrand Nash competition in the Chinese passenger-vehicle industry. No evidence for within or cross-group price collusion is found. In addition, the policy experiments show that indigenous brands will gain market shares and profits if within group companies merge.

Xiao and Ju (2014) explore the effects of consumption-tax and fuel-tax adjustments in the Chinese automobile industry. Applying the model and simulation method of Berry, Levinson and Pakes (1995), they conduct a comparative static analysis of equilibrium prices and sales, fuel consumption, and social welfare before and after tax adjustments. For the first time, they compare the progressivity of both taxes. Their empirical findings suggest that the fuel tax is effective in decreasing fuel consumption at the expense of social welfare, while the consumption tax does not significantly affect either fuel consumption or social welfare.

Li, Xiao and Liu (2015) document the evolution of price and investigate the sources of price decline, paying attention to both market structure and cost factors. They estimate a market equilibrium model with differentiated multiproduct oligopoly using market-level sales data in China together with information from household surveys. Their counterfactual simulations show that (quality-adjusted) vehicle prices have dropped by 33% from 2004 to 2009. The decrease in markup from intensified competition accounts for about one third of this change and the rest comes from cost reductions through learning by doing and other channels.

Liu and Lin Lawell (2015) examine the effects of public transportation and the built environment on the number of civilian vehicles in China. They use a 2-step GMM instrumental variables model and apply it to city-level panel data over the period 2001 to 2011. The results show that increasing the road area increases the number of civilian vehicles. In contrast, increasing the public transit passenger load decreases the number of civilian vehicles. However, the effects vary by city population. For larger cities, increases in the number of public buses increase the number of civilian vehicles, but increases in the number of taxis and in road area decrease the number of civilian vehicles. They also find that land use diversity increases the number of civilian vehicles, especially in the higher income cities and in the extremely big cities. Finally, they find no significant relationship between civilian vehicles and per capita disposable income except in mega cities.

Both market-based and non-market based mechanisms are being implemented in China's major cities to distribute limited vehicle licenses as a measure to combat worsening traffic congestion and air pollution. While Beijing employs non-transferable lotteries, Shanghai uses an auction system. Li (2015) empirically quantifies the welfare consequences of the two mechanisms by taking into account both allocation efficiency and automobile externalities postallocation. His analysis shows that different allocation mechanisms lead to dramatic differences in social welfare. Although the lottery system in Beijing has a large advantage in reducing externalities from automobile use than a uniform price auction, the advantage is offset by the significant welfare loss from misallocation. The lottery system forewent nearly 36 billion RMB (or $6 billion) in social welfare in Beijing in 2012 alone. A uniform-price auction would have generated 21.6 billion RMB to Beijing municipal government, more than covering all the subsidies to the local public transit system.

The fourth strand of literature we build upon is that on mixed oligopoly. A mixed oligopoly is defined as an oligopolistic market structure with a relatively small number of firms for which the objective of at least one firm differs from that of other firms (De Fraja and Delbono, 1990), as opposed to a private oligopoly in which all firms have the objective of profit maximization. Usually in a mixed oligopoly there is a public firm competing with a multitude of profit-maximizing firms (Poyago-Theotoky, 2001).

De Fraja and Delbona (1989) study a situation in which private and public firms compete both using only market instruments. When talking about public and private firms, they think of firms which pursue different objectives. They find that nationalization is always socially better than Stackelberg leadership, which is in turn socially better than Cournot-Nash behavior. If there is no way of avoiding competition with a public firm, private entrepreneurs would prefer the public firm to behave as a Stackelberg leader.

De Fraja and Delbona (1990) examine a case of mixed oligopoly which is particularly interesting from the point of view of economic and industrial policy: a market in which at least one publicly owned firm cohabits which at least one private firm. A market where there are both private and public firms is then a mixed oligopoly because the firms owned by private agents aim to maximize profits, whereas the publicly owned firms are interested in optimizing social targets. There are two broad results which emerge from the models considered in this survey. Firstly, the public authority can fruitfully use the public firms as an instrument towards the achievement of its goals, namely the increase of social welfare. Secondly, in general, it does not seem to be optimal for the public authority to instruct the public firms to take decisions which result in equality between price and marginal cost, either because of a budget constraint, or because the maximum social welfare is reached when price is higher than public marginal cost.

Since previous articles on mixed oligopoly did not include foreign private firms, Fjell and Pal (1996) consider a mixed oligopoly model in which a state-owned public firm competes with both domestic and foreign private firms. The effect on the equilibrium involves a lower price and a different allocation of production. They also discuss issues such as the effects of an open door policy allowing foreign firms to enter and the effects of foreign acquisition of domestic firms.

White (1996) examines the use of output subsidies in the presence of a mixed oligopoly. He finds that if subsidies are used in a simultaneous-moves oligopoly and the industry is subsequently privatized, there is a reduction in social welfare. Moreover, both in the private oligopoly and in the mixed oligopoly, the optimal output subsidy is identical.

Poyago-Theotoky (2001) provide a much stronger "irrelevance" result with respect to firms' moves and market structure in the presence of output subsidization. In addition to a private oligopoly and a mixed oligopoly where all firms make their output decisions simultaneously, they consider the case of the public firms acting as a Stackelberg leader. They show that the optimal output subsidy is identical and profits, output and social welfare are also identical irrespective of whether (i) the public firm moves simultaneously with the private firms or (ii) the public firm acts as Stackelberg leader or (iii) all firms behave as profit-maximizers.

De Fraja (2009) argues that whether a taxpayer financed subsidy to some suppliers (typically the public ones) is tantamount to “unfair” competition should be assessed with the understanding of the nature of the objective function of the providers: behavior which would be deemed anti-competitive for a profit maximizing oligopolist, may be in line with the objective function of a public, welfare-maximizing supplier. On the other hand, where the presence of public suppliers bestows a positive externality on the private suppliers, then a taxpayer financed subsidy distributed assymetrically to the players in the sector according to their ownership may benefit all suppliers, private and public alike.

In Lutz and Pezzino’s (2010) setting, a private and a public firm face fixed quality-dependent costs of production and compete first in quality and then either in prices or in quantities. In the long run the public firm targets welfare maximization whereas the private firm maximizes profits. In the short run both firms compete in prices or quantities to maximize profits. They conclude that mixed competition is always socially desirable compared to a private duopoly regardless of the type of competition in the short run and the equilibrium quality ranking. In addition, mixed competition seems to be a more efficient regulatory instrument than the adoption of a minimum quality standard.

Bennett and La Manna (2012) also consider a mixed oligopoly with free entry by private firms, assuming that a public firm maximizes an increasing function of output, subject to a break-even constraint. An irrelevance result is obtained: whenever a mixed oligopoly is viable, then aggregate output, aggregate costs and welfare are the same with and without the public firm. However, replacing a viable mixed oligopoly with a public monopoly yields higher net welfare.

Haraguchi and Matsumura (forthcoming) revisit the classic discussion comparing price and quantity competition, but in a mixed oligopoly in which one state-owned public firm competes against private firms. It has been shown that in a mixed duopoly, price competition yields a larger profit for the private firm. They adopt a standard differentiated oligopoly with a linear demand and find that regardless of the number of firms, price competition yields higher welfare, however, the profit ranking depends on the number of private firms. They also endogenize the price-quantity choice and find that Bertrand competition can fail to be an equilibrium, unless there is only one private firm.

A related literature is that on the objectives of state-owned firms. Ghandi and Lin (2012) model the dynamically optimal oil production on Iran's offshore Soroosh and Nowrooz fields, which have been developed by Shell Exploration through a buy-back service contract. In particular, they examine the National Iranian Oil Company's (NIOC) actual and contractual oil production behavior and compare it to the production profile that would have been optimal under the conditions of the contract. They find that the contract's production profile is different from optimal production profile for most discount rates, and that the NIOC's actual behavior is inefficient- its production rates have not maximized profits. Because the NIOC's objective is purported to be maximizing cumulative production instead of the present discounted value of the entire stream of profits, they also compare the INOC's behavior to the production profile that would maximize cumulative production. They find that even though what the contract dictates comes close to maximizing cumulative production, the NIOC has not been achieving its own objective of maximizing cumulative production.

4. Econometric Model

A traditional logit model of vehicle demand assumes the independence of irrelevant alternatives, and can therefore generate unrealistic substitution patterns. In a logit model, if you take away a car model from the choice set, then consumers of that car will buy other cars according to their market shares. However, in reality, if you remove, say, a luxury car, the consumers of that luxury car are probably more likely to buy another luxury car than a random consumer would, even if luxury cars have low market share. In contrast, a Berry, Levinsohn and Pakes (1995) random coefficients demand model of vehicle demand addresses this problem by allowing for interactions between unobserved consumer characteristics and observed product characteristics, thus allowing different consumers to vary in how much they like different car characteristics.

Our research builds on the work of Berry, Levinsohn and Pakes (1995), who develop a model for empirically analyzing demand and supply in differentiated products markets and then apply these techniques to analyze the equilibrium in the U.S. automobile industry. Their framework enables one to obtain estimates of demand and cost parameters for a class of oligopolistic differentiated products markets. Unlike traditional logit demand models, their random coefficients model allows for interactions between consumer and product characteristics, thus generating reasonable substitution patterns. Estimates from their framework can be obtained using only widely available product-level and aggregate consumer-level data, and they are consistent with a structural model of equilibrium in an oligopolistic industry. They apply their techniques to the U.S. automobile market, and obtain cost and demand parameters for (essentially) all models marketed over a twenty-year period. On the cost side, they estimate cost as a function of product characteristics. On the demand side, they estimate own- and cross-price elasticities as well as elasticities of demand with respect to vehicle attributes (such as weight or fuel efficiency).

Our research innovates upon the Berry et al. (1995) work by developing a model of the Chinese automobile market; by including alternative vehicles so that in addition to cost and demand parameters relating to gasoline-fueled vehicles, cost and demand parameters relating to alternative vehicles can be estimated; and by modeling the behavior of not only private automobile companies but also the state-owned automobile companies in China.

Let $x_j = \{x_{jk}\}_k$ denote a vector of observable vehicle characteristics *k* for vehicle model $j \in \{1,...,J\}$, ξ_j denote a vector of unobservable vehicle characteristics for vehicle model *j*, p_j denote the price of vehicle model *j*, β_k denote the mean taste parameter for vehicle characteristic *k*, ζ_{ik} denote a characteristic of consumer *i* that affects *i's* taste for vehicle characteristic *k*, and y_i denote consumer *i*'s income. The random coefficients specification for the utility of consumer *i* for vehicle model *j* is given by:

$$u_{ij} = \delta_j + \nu_{ij},$$

where δ_j is the common component of the utility for vehicle model *j* and is given by:

$$\delta_j = x_j \beta - \alpha p_j + \xi_j,$$

and where the first two terms in the idiosyncratic component ν_{ij} interact consumer and product characteristics:

$$\nu_{ij} = \sum_k x_{jk} \sigma_k \zeta_{ik} - \frac{1}{y_i} p_j + \varepsilon_{ij} \ ,$$

where ε_{ij} is distributed type I extreme value. We assume ζ_{ik} has a standard normal distribution so that the mean and variance of the marginal utilities associated with characteristic *k* are β_k and $\sigma_k{}^2$, respectively. We assume income y_i is log normally distributed.

We normalize the deterministic components of the utility for the outside option $j = 0$ of not purchasing a vehicle to 0, so that utility of consumer *i* for the outside option $j = 0$ is given by:

$$u_{i0} = \varepsilon_{i0},$$

where ε_{i0} is distributed type I extreme value.

The share s_j of consumers who purchase vehicle model *j* is therefore given by:

$$s_j = E\left[\frac{\exp\left(\delta_j + \sum_k x_{jk}\sigma_k\zeta_{ik} - \frac{1}{y_i}p_j\right)}{1 + \sum_{j'=1}^{J}\exp\left(\delta_{j'} + \sum_k x_{j'k}\sigma_k\zeta_{ik} - \frac{1}{y_i}p_{j'}\right)}\right],$$

where the expectation is taken over the distribution of the individual characteristics ζ_{ik} and income y_i.

Traditional logit and probit models commonly assume that there are no terms in the idiosyncratic component ν_{ij} that interact consumer and product characteristics (i.e., $\nu_{ij} = \varepsilon_{ij}$) and therefore that the variation in consumer tastes enters only through the additive error term ε_{ij}, which is assumed to be identically and independently distributed across consumers and choices. However, this strong assumption places very strong restrictions on the pattern of cross-price elasticities from the estimated model. All properties of market demand, including market shares and elasticities, are determined solely by the common component of utility δ_j. In the automobile market, for example, this property implies that any pair of cars with the same pair of market shares will have the same cross-price elasticity with any given third product.

In contrast, in a random coefficients demand model, owing to the interaction between consumer preferences and product characteristics in v_{ij}, consumers who have a preference for size will tend to attach a high utility to all large cars, and this will induce large substitution effects between large cars.

The estimation equation on the demand side is the calculated common component of utility δ_j, which is given by the inverse market share function:

$$\delta_j(s_j) = x_j\beta - \alpha p_j + \xi_j,$$

where s_j is the share of consumers who purchase vehicle model *j*. To derive the inverse market share function $\delta_j(s_j)$, we first compute the expected market share function as a function of the common components of utility δ_j, where the expectation is taken over the distribution of consumer characteristics, and then invert the expected market share function to derive the common component of utility δ_j as a function of market share s_j.

The estimation equation on the supply side is given by the pricing equation for good j:

$$p - \Delta^{-1}s = c,$$

where Δ is a matrix in which $\Delta_{jk} = -\frac{\partial s_k}{\partial p_j}$ if *j* and *k* are produced by the same firm and $\Delta_{jk} = 0$ otherwise ; and where the marginal cost c_j is given by:

$$c_j = x_j\gamma + \eta q_j + \omega_j,$$

where ω_j are the unobservable cost variables. On the supply side, we assume a Bertrand (Nash-in-prices) equilibrium among multiproduct firms.

The parameters to be estimated include the means β of the marginal utility associated with each particular characteristic, the parameter α in the marginal disutility of price, the cost parameters γ, the coefficient η on quantity in marginal cost, and the standard deviations σ of the marginal utility associated with each particular characteristic.

Because the observed equilibrium prices and quantities are simultaneously determined in the supply-and-demand system, instrumental variables are needed to address the endogeneity problem (Goldberger, 1991; Manski, 1995; Angrist et al., 2000; Lin, 2011). Since price and the market share variables are endogenous in demand and supply, we use instruments for the endogenous price and market share variables.

The instrumental variables we use in our estimation build on the work of Berry et al. (1995). We construct two different types of instrumental variables based on each car characteristic: the number of cars with similar values of the characteristic, and the value of the characteristic for the car k closest to car j in the value of the characteristic. More specifically, for each characteristic r, the first instrumental variable we create is the number of cars that has similar value of attribute r to car j. Two cars j and k are "similar" in characteristic r if the squared difference in their values of that characteristic is less than or equal to one tenth of the squared difference between the maximum and minimum values of that characteristic among all cars: $(x_{jr} - x_{kr})^2 \le \frac{1}{10}\left(\max(x_r) - \min(x_r)\right)^2$ (except for the car capacity in terms of number of seats, of which the cutoff value is the 2). A second instrumental variable we create for each characteristic r is the value of characteristic r for the car k closest to car j in the value of the characteristic.

The number of cars with similar values of the characteristic, and the value of the characteristic for the car *k* closest to car *j* in the value of the characteristic are good instruments for price in the demand equation because characteristics of other cars *k* of other firms are independent of the utility for a particular car *j*, and because they are correlated with price via the markup in the supply-side first-order conditions. Characteristics of other cars *k* of other firms also serve as good instruments for the market share of car *j* in the supply-side pricing equation.

The demand and supply side equations are jointly estimated using instruments for the endogenous price and market share variables via generalized method of moments.[4] The parameters to be estimated include the means β of the marginal utility associated with each particular characteristic, the parameter α in the marginal disutility of price, the cost parameters γ, the coefficient η on quantity in marginal cost, and the standard deviations σ of the marginal utility associated with each particular characteristic.

Standard errors are formed by a nonparametric bootstrap. Model-displacement-style-years are randomly drawn from the data set with replacement to generate 100 independent pseudo-samples of size equal to the actual sample size. The structural econometric model is run on each of the new pseudo-samples. The standard error is then formed by taking the standard deviation of the estimates from each of the random samples.

5. Data

The annual data set we have collected includes all the models marketed from the year 2004 to year 2013 in the Chinese automobile industry. Within each model, we have collected

[4] One challenge is determining whether the model has converged at a global or local minimum (Knittel and Metaxoglou, 2014). We experimented with several combinations of starting values to initialize the parameters to be estimated in order to find the set of parameters that minimized the weighted sum of squared moments.

information of price and quantity sales of each displacement of that model. Furthermore, for each model displacement, we also gathered information on vehicles characteristics for each style within that model. Since models both appear and exit over the entire time period, we have an unbalanced panel. We treat each style of a model-displacement-year as a single observation. Throughout the paper, each model-displacement-style-year is treated as different observations as long as they differ in any vehicle characteristics.

The quantity sales data from year 2004 to year 2013 of each model displacement was collected from the *China Auto Market Almanac*, which includes the quantity sales of all vehicles sold by car manufactures in China, both indigenous firms and joint ventures. We have collected two sets of price data, both in units of 10,000 RMB. The first price variable was collected from *China Automotive Industry Year book* for each model displacement. The other price variable was grabbed from *www.autohome.com.cn*, which is one of the largest vehicle websites in China. (Other famous and widely used car websites are: *http://auto.sohu.com*, *http://auto.163.com*, *http://auto.sina.com.cn*, *http://auto.qq.com*). The price is listed as nominal manufacturer's suggested retail price (MSRP). It is better to get real transaction price. However, that is usually not easy to find.

After merging the price and quantity sales from the three sources mentioned above, our data set consists of 1601 model-displacement-year observations, representing 531 model displacements. The information about vehicle characteristics was obtained from *www.autohome.com.cn.* For each style of a certain vehicle model displacement, its characteristics could be divided into the following ten categories. (1) Basic information: the year when such vehicle was produced, dummy for vehicle manufacturers, dummy for vehicle type such as sedan, SUV, MPV, pick-up, sports car, etc. (2) Information about vehicle engines: cylinder layout types;

number of cylinders, etc. (3) Information about powertrain: top speed (km/h); acceleration from 0 to 100km/h (in seconds); horsepower (PS); dummy variable for transmission types; number of transmission speeds; types of drivetrain: front engine front drive/ middle engine four-wheel drive, etc.; types of four wheel drive: full time/ real time/ part time; types of power steering: mechanical power steering/ electric power steering etc.; (4) Information about fuel: dummy variable for which type of fuel the vehicle is powered on; fuel efficiency (100km/L), which is the reciprocal of energy intensity (L/100km); displacement (in ml and L); ways of air intake: naturally aspirated, mechanical supercharging; turbo boost, etc.; (5) Dimensions: length, width, height, wheelbase, all in unit mm; number of doors, passenger capacity (number of seats); (6) Safety equipment: this includes a series of dummy variables for whether the vehicle has been equipped or not: frontal driver air bag; side airbag; brake ABS; front radar; rear radar; back up camera; remote control key; keyless active feature; keyless entry feature; (7) Exterior features: dummy variables for whether the vehicle is equipped with electronic sunroof; panorama sunroof. (8) Interior features: dummy variables for the following features: heated front seats; heated rear seats, ventilated front seats; ventilated rear seats; GPS; bluetooth interface; build-in TV; Air conditioner. (9) Advanced technologies: dummy variables for advanced technologies such as park assist; side assist. (10) For alternative fuel vehicles of which electricity is one of the power sources, there is also information about the electric engine: total power of electric engine (kW); the torque of the electric engine (Newton-metre); energy density (kWh) and charge-depleting range (km). Table A1 in the Appendix provides detailed information about all vehicle characteristics variables.

One unique feature of the Chinese automobile industry is that some of the car manufacturers are state owned. Among the 64 car makers in our sample, 49 of them are state owned. As long as the name of the car manufacturers are different in *www.autohome.com.cn,* we treated those manufacturers as different makers. Additionally, since the majority of car companies in China are operated under shareholding system, in a strict sense, there are few state owned car companies. However, governments do hold a majority of the stocks of some of the companies. Throughout the paper, a stated owned firm is defined as a car manufacturer of which a majority of stock of its parent company (greater than 50%) is held by governments (either central government or local government), although some of its stock might be held by foreign companies such as those joint venture firms. Information about the ownership of the car companies are referred from *baike.baidu.com* which is used to track back their parent companies, and from *China Industry Business Performance Data of year 2013* as well.

In addition, we have collected data on the adult population (age 15-64) from year 2000 to 2014 from *World Development Indicators* to proxy the automobile market size. Information about urban income across all provinces of year 2010 to 2013 are gathered from *China Statistical Year Book.*

Table 1 presents summary statistics of the variables in our data set.

We start with a brief discussion of the summary statistics of the five characteristics variables we have chosen for our preliminary estimation. They are fuel efficiency, length, weight, passenger capacity (in terms of the number of seats), and horsepower. Unlike in the U.S., where the measurement of fuel efficiency is mileage per gallon, China uses a fuel consumption measurement of liters per 100 kilometers to evaluate the energy density (the smaller the value is, the better in terms of energy efficiency). Therefore, we use a reciprocal of that measurement, which is 100 kilometers per liter of gas to evaluate energy intensity. The mean is 0.131 100km/L, with a standard deviation of 0.02, minimum of 0.752 100km/L and maximum of 0.233 100km/L.

The average length is 4456.209 mm, with a minimum of 3400 mm and maximum of 6870 mm. Its standard deviation is 359.680. The average weight is 1345.930 kg, the median is 1324 kg, 95% of the vehicles in our sample has a weight below 1800 kg. The average passenger capacity is 5 seats. The minimum is 2 seats and maximum is 5 seats. Average horsepower is 130.226 PS, and the minimum and maximum are 970 PS and 4700 PS, respectively.

Regarding alternative fuel vehicles, we have 28 model-displacement-style-year observations in total which are powered by alternative fuel sources. These alternative fuel vehicles include hybrid cars powered on both gasoline and electricity, purely electric cars, plug in hybrid cars, and extended range electric vehicles. Of these, 21 model-displacement-style-years were produced after 2010. In the year 2010, the Chinese government established a project called "Energy Saving Projects", using a fiscal subsidy to encourage energy saving. Some autos with small displacement (less than 1.6L) will receive a subsidy (directly to the car makers) such that the market price is the price after subsidized. We will evaluate the effects of this policy on supply and demand. It is possible that this policy encourages the production of vehicles with small displacement.

6. Preliminary Results

5.1 Model with interactions between consumer preferences and price

We start with a model in which we focus on the interaction between consumer preferences measured by income and the product characteristic of price. In this model, we estimate the means β of the marginal utility associated with each particular characteristic, but assume that the standard deviations σ of the marginal utility associated with each particular characteristic are 0. We therefore assume that the interactions ν_{ij} between consumer preferences and product characteristic take the following special case:

$$\nu_{ij} = -\frac{1}{y_i} p_j + \varepsilon_{ij} .$$

We estimate our model using the data from 2010 to 2013. We select the following five vehicle characteristics in the estimation technique, both in the demand and pricing equations: fuel efficiency, length, weight, passenger capacity (number of seats), and horsepower. Fuel efficiency and horsepower are measurements of the engine. Weight and length are proxies of safety, while capacity proxies interior specification. One of our extensions of the Berry, Levinsohn and Pakes (1995) model is that we add a dummy for the vehicle being powered by alternative fuels, which in our data set includes hybrid vehicles, electric vehicles, plug-in hybrids, and extended range electric vehicles. Also, as a first step towards a mixed oligopoly model, we compare our estimation results with and without including the state-owned dummy variable in the supply-side pricing equation. The results are reported in Table 2.

Specification (1) of Table 2 reports the results without including the state-owned dummy variable in the supply-side pricing equation. The means of the marginal utility of fuel efficiency, length, weight are positive and statistically significant at a level of 0.1%. The mean of the marginal utility of capacity is significant at a level of 1% while that of horsepower is not significant. An even more interesting finding is that we have positive and significant mean marginal utility for the vehicle being powered on alternative energy sources. The parameter α in the marginal disutility of price is positive statistically significant and large in magnitude.

On the cost side, the coefficients in marginal cost on the dummy for alternative vehicle, length, weight, and capacity are positive and statistically significant at a level of 0.1%, which indicates improvements on these characteristics will increase the marginal cost. The coefficient on quantity in marginal cost is positive and statistically significant.

Specification (2) of Table 2 reports the results when we include the state-owned dummy variable in the supply-side pricing equation. For the demand-side parameters, all the demand parameter estimates are smaller in magnitude when we include the state-owned dummy variable in the supply-side pricing equation. The parameter α in the marginal disutility of price is also smaller in magnitude.

On the cost side, all the coefficients in marginal cost on the attributes except weight are smaller in magnitude when we include the state-owned dummy variable in the supply-side pricing equation. Still the coefficient on fuel efficiency is insignificant. The coefficient on quantity in marginal cost is smaller but still insignificant. The coefficient on state-owned is positive and significant, indicating that state-owned automobile companies have higher marginal cost than private automobile companies do.

5.2 Model with full set of interactions between consumer preferences and product characteristics

We now estimate the full model with a full set of interactions between consumer preferences and product characteristics. In particular, we now estimate both the means β of the marginal utility associated with each particular characteristic, as well as the standard deviations σ of the marginal utility associated with each particular characteristic. Once again, as a first step towards a mixed oligopoly model, we compare our estimation results with and without including the state-owned dummy variable in the supply-side pricing equation. The results are reported in Table 3.

There are in general two ways to explain, for example why consumers prefer the vehicle with higher horsepower. Both an increase in the mean and an increase in the variance of tastes will increase the share of consumers who purchase cars with high horsepower. However, these two explanations have different implications. If there were for example, a zero standard deviation for the distribution of marginal utilities of horsepower, we would find that when a high horsepower car increases its price, consumers who substitute away from that car have the same marginal utilities for horsepower as any other consumer and that car have the same marginal utilities for horsepower as any other consumer and hence will not tend to substitute disproportionately toward other high horsepower cars. However, if on the other hand, the standard deviation of tastes for horsepower was relatively large, the consumers who substitute away from the high horsepower cars will tend to substitute disproportionately towards other high horsepower cars.

Specification (1) of Table 3 reports the results without including the state-owned dummy variable in the supply-side pricing equation. The means of the marginal utility of the chosen car attributes, including the alternative vehicle dummy, fuel efficiency, length, weight, capacity and horsepower are all positive and significant.

The standard deviations of the marginal utility of fuel efficiency, length, weight, capacity, and horsepower are positive and statistically significant, which indicates that there is a distribution of tastes for these characteristics, with some people preferring a higher level, while some others preferring a lower level. Similarly, the standard deviation of the marginal utility of the alternative vehicle dummy is significant and positive as well, indicating a distribution of tastes for alternative vehicles. The parameter α in the marginal disutility of price is positive and significant.

On the cost side, the cost coefficients in marginal cost on all of the chosen car attributes are positive and statistically significant.

Specification (2) of Table 3 reports the results when we include the state-owned dummy variable in the supply-side pricing equation. The means of the marginal utility of the chosen car attributes, including the alternative vehicle dummy, are all positive and significant. Except for the coefficient on the length and that on capacity, all the other demand coefficients are larger in magnitude when we include the state-owned dummy variable in the supply-side pricing equation. What's interesting is that, the mean of the marginal utility of capacity is negative and significant.

The standard deviations of the marginal utility of fuel efficiency, length, weight, capacity, and horsepower are positive and statistically significant, which indicates that there is a distribution of tastes for these characteristics, with some people preferring a higher level, while some others preferring a lower level. For car capacity, while on average people prefer cars with fewer seats, there is a distribution of tastes, with some people preferring cars with more seats and other prefer ones with fewer seats.

On the cost side, all the coefficients corresponding to the attributes are positive and statistically significant. Also, the coefficient on the ownership dummy is significant.

7. Next Steps

The next steps of our research include:

(1) Try other characteristic variables.

Since we have tried only a few car characteristics such as fuel efficiency, length, weight, capacity, horsepower, and a dummy for the vehicle being powered by alternative fuels, and since in our data set we have a wide variety of vehicle characteristic variables, we will include different sets of characteristics.

(2) Estimate the models using all years of data.

Our data set is a panel data set that follows car models over all years they are marketed. It is likely that the demand and cost disturbances of a given model are more similar across years than are the disturbances of different models. Although correlations in the disturbance would not affect consistency, nor normality, they do affect the variance covariance matrix. We will run our structural model using the years 2010-2013, and treat the sum of the moment restrictions of a given model over time as a single observation, in which way it produces standard errors that allow for arbitrary correlation across years for a given model and arbitrary heteroscedasticity across models.

(3) Implement new innovations and refinements to the Berry et al. (1995) model.

We will draw from the literature building on the Berry et al. (1995) model (Petrin, 2002; Berry, Levinsohn and Pakes, 2004; Dube, Fox and Su, 2012; Berry and Haile, 2014; Berry and Haile, 2015; Bajari et al., 2015) and implement new innovations and refinements to the Berry et al. (1995) model.

(4) Analyze mixed oligopoly.

We will draw from the literature on mixed oligopoly (De Fraja and Delbono, 1989; De Fraja and Delbono, 1990; Fjell and Pal, 1996; Poyago-Theotoky, 2001; De Fraja, 2009; Lutz and

Pezzino, 2010; Bennett and La Manna, 2012; Haraguchi and Matsumura, forthcoming) to better model the state-owned firms and their interactions with the private firms.

(5) Analyze the distribution of marginal utility.

We will analyze the distribution of marginal utility to assess the demand for alternative vehicles. For example, we will compare the marginal utilities for fuel efficiency with the marginal utilities for alternative vehicles to see if there is any marginal utility for alternative vehicles beyond the benefits they provide in terms of increased fuel efficiency.

(6) Simulate the effects of introducing new vehicles.

We will simulate the effects of introducing new vehicles, including new alternative vehicles, which are novel combinations of car characteristics, on supply and demand.

(7) Simulate the effects of government policy.

We will simulate the effects of government policy on supply and demand, including demand for alternative vehicles. As described earlier, in the year 2010, the Chinese government established a project called "Energy Saving Projects", using a fiscal subsidy to encourage energy saving. Some autos with small displacement (less than 1.6L) will receive a subsidy (directly to the car makers) such that the market price is the price after subsidized. We will further expand our data set by adding the information about a vehicle qualified for the subsidy or not. We will simulate the effects of the government subsidy on supply and demand, including demand for alternative vehicles. We will also simulate the effects of other alternative government policies on supply and demand, including demand for alternative vehicles.

(8) Add dynamics to both the demand and supply side.

On the demand side, we will add dynamics by allowing the consumer vehicle choice decision to by dynamic. On the supply side, we will model the dynamic decisions of automobile companies of which cars to produce and which new cars to introduce as a dynamic game. With this more sophisticated model, we will then simulate the effects of various counterfactual scenarios and government policies on supply, demand, and the introduction of new cars, including new alternative vehicles.

References

Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin, and John Van Reenen. (2016). Carbon taxes, path dependency and directed technical change: Evidence from the auto industry. Journal of Political Economy, 124 (1), 1-51.

Anderson, S.T., and J.M. Sallee. (forthcoming). Designing policies to make cars greener: A review of the literature. Annual Review of Resource Economics.

Angrist, J., K. Graddy, and G.W. Imbens. (2000). The interpretation of instrumental variables estimators in simultaneous equations models with an application to the demand for fish. Review of Economic Studies, 67 (3), 499-527.

Bajari, P., D. Nekipelov, S.P. Ryan, and M. Yang. (2015). Demand estimation with machine learning and model combination. Working paper, University of Washington.

Bennett, John, and Manfredi La Manna. (2012). Mixed oligopoly, public firm behavior, and free private entry. Economics Letters, 117, 767-769.

Beresteanu, A., and S. Li. (2011). Gasoline prices, government support, and the demand for hybrid vehicles in the United States. International Economic Review, 52 (1), 161-182.

Berry, S. (1994). Estimating discrete choice models of product differentiation. RAND Journal of Economics, 25 (2), 242-262.

Berry, S.T. and P.A. Haile. (2014). Identification in differentiated products markets using market level data. Econometrica, 82 (5), 1749-1797.

Berry, S.T. and P.A. Haile. (2015). Identification in differentiated products markets. Cowles Foundation Discussion Paper No. 2019.

Berry, S., J. Levinsohn, and A. Pakes. (1995). Automobile prices in market equilibrium. Econometrica, 63 (4), 841-890.

Berry, S., J. Levinsohn, and A. Pakes. (2004). Differentiated products demand systems from a combination of micro and macro data: The new car market. Journal of Political Economy, 112 (1), 68-105.

Bresnahan, T. (1982). The oligopoly solution concept is identified. Economics Letters, 10, 87-92.

Darido, G., M. Torres-Montoya and S. Mehndiratta. (2014). Urban transport and CO_2 emissions: Some evidence from Chinese cities. Wiley Interdisciplinary Review: Energy and Environment, 3 (2), 122-155.

De Fraja, G. (2009). Mixed oligopoly: Old and New. University of Leicester Department of Economics. Working Paper No. 09/20.

De Fraja, G., and F. Delbono. (1989). Alternative strategies of a public enterprise in oligopoly. Oxford Economic Papers, 41, 302-311.

De Fraja, G., and F. Delbono. (1990). Game-theoretic models of mixed oligopoly. Journal of Economic Surveys, 4, 1-17.

Dube, J.-P., J.T. Fox, and C.-L. Su. (2012). Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation. Econometrica, 80 (5), 2231-2267.

Feenstra, R.C., and J. Levinsohn. (1995). Estimating markups and market conduct with multidimensional product attributes. Review of Economic Studies, 62, 19-52.

Fjell, Kenneth, and Debashsis Pal. (1996). A mixed oligopoly in the presence of foreign private firms. Canadian Journal of Economics, 29 (3), 737-743.

Gallagher, K.S. and E. Muehlegger. (2011). Giving green to get green?: Incentives and consumer adoption of hybrid vehicle technology. Journal of Environmental Economics and Management, 61, 1-15.

Ghandi, Abbas, and C.-Y. Cynthia Lin. (2012). Do Iran's buy-back service contracts lead to optimal production?: The case of Soroosh and Nowrooz. Energy Policy, 42, 181-190.

Goldberg, P.K. (1995). Product differentiation and oligopoly in international markets: The case of the U.S. automobile industry. Econometrica, 63 (4), 891-951.

Goldberger, A.S. (1991). A Course in Econometrics. Cambridge, MA: Harvard University Press.

Haraguchi, Junichi, and Toshihiro Matsumura. (forthcoming). Cournot-Bertrand comparison in a mixed oligopoly. Journal of Economics.

Heutel, G., and E. Muehlegger. (2015). Consumer learning and hybrid vehicle adoption. Environmental and Resource Economics, 62, 125-161.

Hoderlein, S., J. Klemela, and E. Mammen. (2010). Analyzing the random coefficient model nonparametrically. Econometric Theory, 26 (3), 804-837.

Hu, Wei-Min, Junji Xiao, and Xiaolan Zhou. (2014). Collusion or Competition? Interfirm Relationships in the Chinese Auto Industry. Journal of Industrial Economics, 62 (1), 1-40.

Huo, H., M. Wang, L. Johnson, and D. He. (2007). Projection of Chinese Motor Vehicle Growth, Oil Demand, and C02 Emissions through 2050. Transportation Research Record, 2038, 69-77.

Jacobsen, Mark R. (2013). Evaluating U.S. Fuel Economy Standards in a Model with Producer and Household Heterogeneity. American Economic Journal: Economic Policy, 5 (2), 148-187.

Jacobsen, M.R. and A.A. van Benthem (2015). Vehicle Scrappage and Gasoline Policy. American Economic Review, 105 (3), 1312-1328.

Knittel, C.R., and K. Metaxoglou. (2014). Estimation of random-coefficient demand models: Two empiricists' perspective. Review of Economics and Statistics, 96 (1), 34-59.

Li, Shanjun. (2015). Better lucky than rich?: Welfare analysis of automobile license allocations in Beijing and Shanghai. Working paper, Cornell University.

Li, S., J. Xiao, and Y. Liu. (2015). The price evolution in China's automobile market. Journal of Economics & Management Strategy, 24 (4), 786-810.

Li, S. and Y. Zhou. (2015). Dynamics of technology adoption and critical mass: The case of the U.S electric vehicle market. Working paper, Cornell University.

Lin, C.-Y.C. (2011). Estimating supply and demand in the world oil market. Journal of Energy and Development, 34 (1), 1-32.

Lin, C.-Y. Cynthia, and Jieyin (Jean) Zeng. (2013). The elasticity of demand for gasoline in China. Energy Policy, 59, 189-97.

Lin, C.-Y. Cynthia, and Jieyin (Jean) Zeng. (2014). The optimal gasoline tax for China. Theoretical Economics Letters, 4 (4), 270-278.

Liu, Qingchun, and C.-Y. Cynthia Lin Lawell. (2015). The effects of public transportation and the built environment on the number of civilian vehicles in China. Working paper, University of California at Davis.

Lutz, Stefan, and Mario Pezzino. (2010). Mixed oligopoly, vertical product differentiation and fixed quality-dependent costs. The University of Manchester Economics Discussion Paper Series EDP-1015.

Manski, C.F. (1995). Identification Problems in the Social Sciences. Cambridge, MA: Harvard University Press.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. Journal of Political Economy, 110 (4), 705-729.

Poyago-Theotoky, J. (2001). Mixed oligopoly, subsidization and the order of firms' moves: An irrelevance result. Economics Bulletin, 12 (3), 1-5.

Reynaert, Mathias, and Frank Verboven. (2014). Improving the performance of random coefficients demand models: The role of optimal instruments. Journal of Econometrics, 179 (1), 83-98.

Sallee, J.M. (2011). The surprising incidence of tax credits for the Toyota Prius. American Economic Journal: Economic Policy, 3, 189-219.

Sallee, J.M., and J. Slemrod. (2012). Car notches: Strategic automaker responses to fuel economy policy. Journal of Public Economics, 96, 981-999.

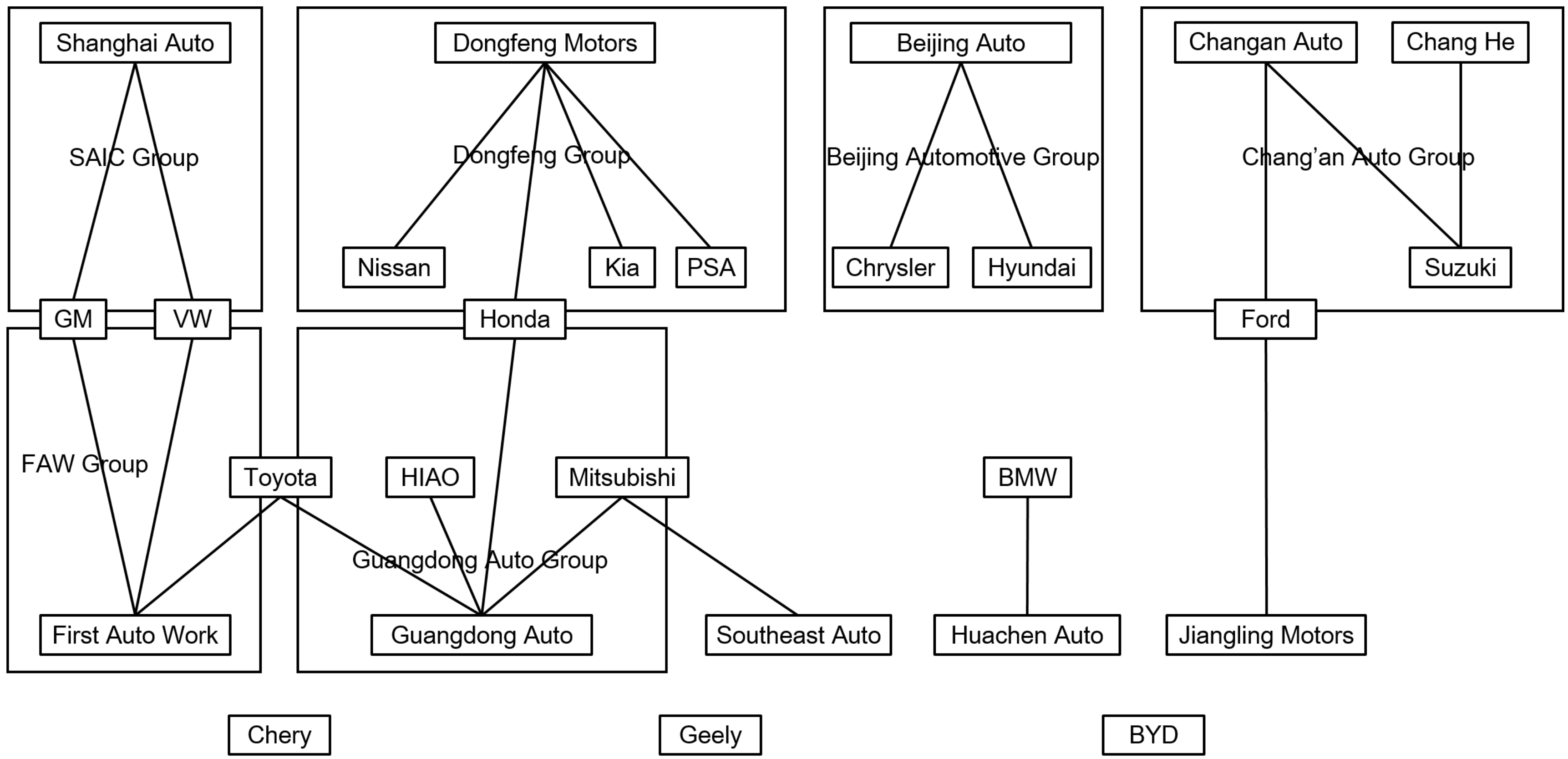
Sallee, J.M., S.E. West, and W. Fan (forthcoming). Do consumers recognize the value of fuel economy: Evidence from used car prices and gasoline price fluctuations. Journal of Public Economics.

Wang, Y., J. Teter, and D. Sperling. (2011). China's soaring vehicle population: Even greater than forecasted? Energy Policy, 39, 3296-3306. URL: http://www.sciencedirect.com/science/article/pii/S030142151100200X

White, M.D. (1996). Mixed oligopoly, privatization and subsidization. Economics Letters, 53, 189-195.

Xiao, Junji, and Heng Ju. (2014). Market equilibrium and the environmental effects of tax adjustments in China's automobile industry. Review of Economics and Statistics, 96 (2), 306-317.

Figure 1: Market Structure of Chinese Automobile Industry



Source: Hu, Xiao and Zhou (2014)

Figure 2: Geographical location of Chinese automobile companies

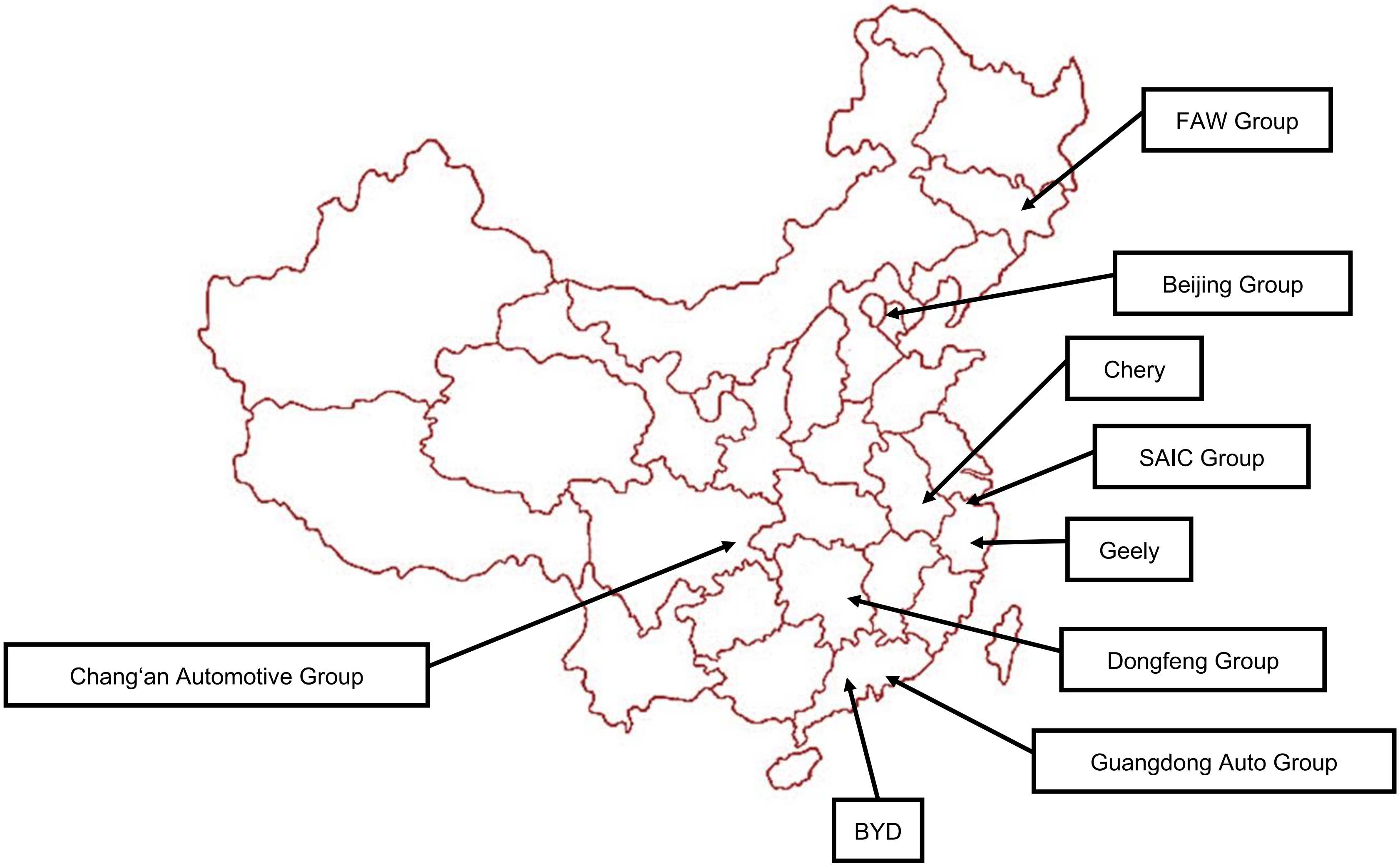


Table 1: Summary Statistics

Variable	# Obs	Mean	Std. Dev.	Min	Max
Year	6821	2009.727	2.677	2004	2013
Model-displacement	6821	270.393	149.588	1	531
Manufacturer's suggested retail price (MSRP) (10,000 yuan)	6821	14.937	10.946	2.88	89.96
Dummy for car manufactures	6803	32.230	17.452	1	64
Model style					
Category of the model style	6821	4.300	2.844	1	13
Dummy variable if the model style is imported	6821	0	0	0	0
Body styles	6821	4.396	3.122	2	11
Minimum price of model style within each model-displacement-year (10,000 yuan)	3608	11.821	8.051	2.68	53.8
Maximum price of model style within each model-displacement-year (10,000 yuan)	3610	18.361	14.713	3.8	89.95
Engine type by the manufacturers					
Cylinder layout types	6798	1.056	0.231	1	2
Number of cylinders	6794	4.128	0.539	3	8
Total power of the electric engine (Kw)	26	49.096	37.512	12	105
The torque of the electric engine (Newton-meter)	24	196.625	130.227	60	450
Energy density (kwh)	6	19.167	18.809	10	57
Charge-depleting Range (km)	6	136.667	80.416	100	300
Maximum volume (km/h)	5588	182.396	22.857	110	265
Official acceleration 0-100km/h (second)	2598	11.626	2.818	5	35
Peak horsepower (PS)	6802	130.246	38.940	16	350
Maximum power (Kw)	6817	95.754	28.626	12	257
Transmission types	6804	1.717	1.003	0	5
Number of transmission speeds	6815	5.190	1.009	1	9
Type of drivetrain	6805	1.207	0.537	1	3
Types of the four wheel drive	417	2.122	0.751	1	3
Type of power steering	6798	2.838	1.314	0	5
Type of fuel that this model is powered on	6805	1.981	0.175	1	4

Official energy density (L/100km)	6	19.167	18.809	10	57
Official fuel intensity (100km/L)	3928	0.131	0.021	0.075	0.233
Alternative vehicle (dummy)	3928	0.004	0.064	0.000	1.000
Displacement (ml)	6673	1795.832	449.240	970	4700
Displacement (L)	6815	1.808	0.456	1	4.7
Different ways of delivering air into the combustion	6798	1.268	0.679	1	3
Length (mm)	6821	4456.209	359.680	3400	6870
Width (mm)	6821	1755.911	78.352	1495	1997
Height (mm)	6821	1533.149	118.915	1325	1937
Wheelbase (mm)	6815	2630.707	158.776	2296	4950
Curb weight (kg)	5898	1346.930	255.769	815	2940
Number of doors	6807	4.449	0.519	2	5
Passenger capacity in terms of number of seats	6811	5.118	0.506	4	9
Airbag: frontal-driver	6819	0.916	0.306	0	2
Airbag: Side airbag	6820	0.869	0.366	0	2
Brake ABS	6811	0.946	0.239	0	2
Parking distance control/radar-front	6821	0.084	0.288	0	2
Parking distance control/radar-rear	6820	0.627	0.524	0	2
Back up camera	6821	0.174	0.430	0	2
Remote control key	6816	0.886	0.324	0	2
Keyless active	6821	0.163	0.379	0	2
Keyless entry	6821	0.101	0.310	0	2
Electronic sunroof	6821	0.583	0.581	0	2
Panorama sunroof	6821	0.035	0.204	0	2
Heated front seats	6821	0.225	0.476	0	2
Heated rear seats	6821	0.031	0.184	0	2
Ventilated front seats	6821	0.022	0.171	0	2
Ventilated rear seats	6821	0.003	0.066	0	2
GPS	6821	0.279	0.560	0	2
Bluetooth interface	6821	0.234	0.492	0	2
Build in TV	6821	0.031	0.195	0	2
Air conditioner	6821	15.413	5.110	0	21
Park assist	6821	0.014	0.139	0	2

Side assist	6821	0.015	0.146	0	2
Adult population (age 15-64) every year	6821	73.068	0.609	71.065	73.507
Mean of log urban income across all provinces every year (yuan)	4374	4.306	0.102	3.995	4.396
Standard deviation of log urban income across all provinces every year	4374	0.099	0.003	0.096	0.106
Dummy for state-owned enterprise	6821	.678	.4672	0	1

Table 2. Results of model with interactions between consumer preferences and price, year 2010-2013

	(1)	(2)
Mean β of marginal utility of:		
Alternative vehicle (dummy)	0.48***	0.39***
	(0.054)	(0.087)
Fuel efficiency (100km/L)	0.49***	0.45***
	(0.049)	(0.074)
Length (mm)	0.36***	0.33***
	(0.081)	(0.060)
Weight (kg)	0.46***	0.43***
	(0.069)	(0.082)
Capacity (number of seats)	0.2**	0.19***
	(0.075)	(0.047)
Horsepower (PS)	0.02	0.02
	(0.067)	(0.078)
Constant	0.51***	0.43***
	(0.060))	(0.055)
Parameter α in marginal disutility of price (1,000 yuan)	0.30***	0.23 **
	(0.054)	(0.073)
Coefficient γ in marginal cost on:		
Alternative vehicle (dummy)	0.30***	0.30***
	(0.063)	(0.057)
Fuel efficiency (100km/L)	0.05	0.02
	(0.066)	(0.073)
Length (mm)	0.46***	0.39***
	(0.050)	(0.077)
Weight (kg)	0.46***	0.50***
	(0.050)	(0.051)
Capacity (number of seats)	0.45***	0.44***
	(0.051)	(0.054)
Horsepower (PS)	0.70***	0.6***
	(0.058)	(0.072)
State-owned (dummy)		0.48***
		(0.078)
Constant	0.70***	0.60***
	(0.050)	(0.073)
Coefficient η on quantity in marginal cost	0.008	0.003
	(0.033)	(0.023)
# Observations	2215	2215

tes: Standard errors are reported in parentheses. Significance codes: * p<0.05; ** p<0.01; ***p<0.001

Table 3. Results of model with full set of interactions between consumer preferences and product characteristics, year 2010-2013

	(1)	(2)
Mean β of marginal utility of:		
Alternative vehicle (dummy)	0.19 ***	0.7 ***
	(0.025)	(0.004)
Fuel efficiency (100km/L)	0.05 *	0.6 ***
	(0.021)	(0.012)
Length (m)	0.16 ***	0.15 ***
	(0.033)	(0.007)
Weight (metric ton)	0.17 ***	0.38 ***
	(0.032)	(0.006)
Capacity (number of seats)	0.04	-0.13 ***
	(0.029)	(0.004)
Horsepower (PS)	0.21 ***	0.37 ***
	(0.023)	(0.003)
Constant	0.08 *	0.15 ***
	(0.032)	(0.001)
Standard deviation σ of marginal utility of:		
Alternative vehicle (dummy)	0.16 ***	0.2 ***
	(0.042)	(0.004)
Fuel efficiency (100km/L)	0.45 ***	0.42 ***
	(0.055)	(0.005)
Length (m)	0.51 ***	0.02 ***
	(0.054)	(0.004)
Weight (metric ton)	0.23 ***	0.25 ***
	(0.028)	(0.005)
Capacity (number of seats)	0.03	0.48 ***
	(0.021)	(0.010)
Horsepower (0.01PS)	0.35 ***	0.33 ***
	(0.044)	(0.007)
Constant	0.08 ***	0.4 ***
	(0.027)	(0.005)
Parameter α in marginal disutility of price (10,000 yuan)	0.48 ***	0.33 ***
	(0.057)	(0.005)
Coefficient γ in marginal cost on:		
Alternative vehicle (dummy)	0.23 ***	0.45 ***
	(0.027)	(0.003)
Fuel efficiency (100km/L)	0.29 ***	0.28 ***
	(0.046)	(0.002)
Length (m)	0.07 ***	0.19 ***
	(0.019)	(0.006)
Weight (metric ton)	0.17 ***	0.02 ***
	(0.034)	(0.004)
Capacity (number of seats)	0.36 ***	0.7 ***

	(0.041)	(0.004)
Horsepower (0.01PS)	0.6 ***	0.15 ***
	(0.061)	(0.006)
State-owned (dummy)		0.11 ***
		(0.012)
Constant	0.16 ***	0.13 ***
	(0.026)	(0.006)
Coefficient η on quantity in marginal cost	0.01 ***	0.001 **
	(0.002)	(0.000)
# Observations	2215	2215

Notes: Standard errors are reported in parentheses. Significance codes: * p<0.05; ** p<0.01; ***p<0.001.

Appendix

Table A1: Variable Description

	Variable	Units	Values
Basic Information	The year of the model style		
	Model-displacement		
	Manufacturer's suggested retail price	10,000 RMB	
	Dummy for Car manufactures		
	Model style		
	Car manufacturer name		
	Category of the model style		1=Mini Car 2=Small Car 3=Compact Car 4=Medium Car 5=Medium-Large Car 6=Large Car 7=Small SUV 8=Compact SUV 9=Medium SUV 10=Medium-Large SUV 11=Large SUV 12=MPV 13=Sports Car 14=Advanced Pickup
	Dummy variable if the model style is import		1=Yes; 0=No

	Body styles		2=2 boxes 3=3 boxes 4=Liftback 5=Wagon 6=Sports Car 7=Sporty car with hard roof 8=Convertible with hardtop 9=Convertible with a folding textile roof 10=SUV 11=MPV 12=Pickup
Price variables	The minimum price of the model style within each model-displacement-year		
	The maximum price of the model style within each model-displacement-year		
Quantity variable			
Engine	Engine type by the manufacturers		
	Cylinder layout types		1=L 2=V 3=W 4=H 5=R
	Number of cylinders		
Electric Engine	Total power of the electric engine	kW	
	The torque of the electric engine	Newton-metre	
	Energy density	kWh	
	Charge-Depleting Range	km	
Powertrain	Maximum volume	km/h	

	Official Acceleration 0-100km/h	second	
	Peak Horsepower	PS	
	Maximum Power	Kw	
	Transmission types		1=MT, 2=AT, 3=DCT, 4=AMT, 5=CVT
	Number of transmission speeds		
	Type of Drivetrain		1=Front engine front drive 2=Front engine rear drive 3=Front engine four-wheel drive 4=Middle engine rear drive 5=Middle engine four-wheel drive 6=Rear engine rear drive 7=Rear engine four drive 8=Double electric four-wheel drive
	Types of the four wheel drive		1=Full time 2=Real time 3=Part time
	Type of Power steering		0=No power steering 1=MPS(Mechanical power steering" 2=HPS 3=EHPS 4=Electric Steer by wire 5=EPS(Electric Power Steering)

Fuel	The type of fuel that this model is powered on		1=Diesel 2=Gasoline 3=Hybrid of gas and electricity 4=Pure electric 5=Plug in hybrid 6=Extended range electric vehicle(E-REV)
	Official energy density	L/100km	
	Official Energy Efficiency	100km/L	
	Displacement	ml	
	Displacement	L	
	Different ways of delivering air into the combustion		1=Naturally aspirated 2=Mechanical supercharging 3=Turbo Boost 4=Mechanical supercharging and Turbo supercharging 5=Twin-turo/biturbo 6=Four-turbo
Dimension	Length	mm	
	Width	mm	
	Height	mm	
	Wheelbase	mm	
	Curb weight	kg	
	Number of doors		
	Passenger Capacity	number of seats	
Safety	Airbag: Frontal-Driver		1=Yes; 0=No; 2=Optional
	Airbag: Side airbag		1=Yes; 0=No; 2=Optional
	Brake ABS		1=Yes; 0=No; 2=Optional
	Parking distance control/Radar-Front		1=Yes; 0=No; 2=Optional

	Parking distance control/Radar-Rear		1=Yes; 0=No; 2=Optional
	Back up camera		1=Yes; 0=No; 2=Optional
	Remote control key		1=Yes; 0=No; 2=Optional
	Keyless active		1=Yes; 0=No; 2=Optional
	Keyless entry		1=Yes; 0=No; 2=Optional
Exterior	Electronic sunroof		1=Yes; 0=No; 2=Optional
	Panorama sunroof		1=Yes; 0=No; 2=Optional
Interior	Heated front seats		1=Yes; 0=No; 2=Optional
	Heated rear seats		1=Yes; 0=No; 2=Optional
	Ventilated front seats		1=Yes; 0=No; 2=Optional
	Ventilated rear seats		1=Yes; 0=No; 2=Optional
	GPS		1=Yes; 0=No; 2=Optional
	Bluetooth interface		1=Yes; 0=No; 2=Optional
	Build in TV		1=Yes; 0=No; 2=Optional
	Air conditioner		Manually=11; Manually(optional)=12; Automatic=21; Automatic(optional)=22; 0=No
New Technology	Park Assist		1=Yes; 0=No; 2=Optional
	Side Assist		1=Yes; 0=No; 2=Optional
Population	The adult population (age 15-64) every year. Source: World Development Indicators.		
Income	Urban income across all provinces every year. (2000,2005,2010, 2011,2012,2013) Source: China Statistical Yearbook		

	The standard deviation of urban income across all provinces every year. (2000,2005,2010, 2011,2012,2013) Source: China Statistical Yearbook		
SOE	Dummy for State Owned Enterprise Information referred from: baike.baidu.com and China Industry Business Performance Data of the year 2013.		1=if governments (central government or local government) holding the majority of the company stocks. (greater than 50%) 0=Privately owned