THE JOURNAL OF INDUSTRIAL ECONOMICS 0022-1821
Volume LXII March 2014 No. 1

COLLUSION OR COMPETITION? INTERFIRM RELATIONSHIPS IN THE CHINESE AUTO INDUSTRY*

Wei-Min Hu†
Junji Xiao‡
Xiaolan Zhou§

The Chinese passenger-vehicle industry contains a large number of manufacturers. Some of them are members of big corporate groups centered around state owned enterprises. These corporate relationships may facilitate collusion. This paper applies the non-nested hypothesis test methodology to data on passenger vehicles to identify whether price collusion exists within corporate groups or across groups. Our empirical results support the assumption of Bertrand Nash competition in the Chinese passenger-vehicle industry: We find no evidence for within or cross-group price collusion. Our policy experiments show that indigenous brands will gain market shares and profits if within-group companies merge.

I. INTRODUCTION

The Chinese automobile industry has experienced rapid development in the last two decades; in particular, the sale of passenger vehicles has been increasing by an annual growth rate of 20%. Since November, 2009, it has been the largest global vehicle market, with annual sales of passenger cars exceeding ten million. As a pillar industry of China, it has attracted growing attention among researchers.[1]

*We thank the Editor and referees for their useful suggestions. Also, we thank Jimmy Chan, Yongmin Chen, Zhiqi Chen, Han Hong, Cheng-Zhong Qin, Matthew Shum, Guofu Tan, and Bingyong Zheng for their suggestions and very helpful comments. All remaining errors are ours. Financial support from The Innovation Program of the Shanghai Municipal Education Commission (grant 14ZSO77) and The National Natural Science Foundation of China (grant 71371116) is gratefully acknowledge.

†Authors' affiliations: Department of Public Finance, National Chengchi University NO. 64, Sec. 2, ZhiNan Road, Wenshan District, Taipei City 11605, Taiwan.
e-mail: weiminhu@nccu.edu.tw

‡Corresponding author, School of Management, Fudan University, RM 332 Siyuan Building, 670 Guoshun Rd., Shanghai, China.
e-mail: junjixiao@fudan.edu.cn.

§School of Economics, Shanghai University of Finance and Economics, and the Key Laboratory of Mathematical Economics (SUFE), Ministry of Education, 777 Guoding Road., Shanghai, China.
e-mail: xiaolan.zhou@mail.shufe.edu.cn

[1] Wang [2003] presents foreign direct investment and policy reforms; Holweg, Luo and Oliver [2009] introduce history, policy, and the market structure of the Chinese automotive industry; Deng and Ma [2010] investigate the market power and profitability of manufacturers; and Xiao and Ju [2011] study the environmental and welfare effects of tax policies.

The structure of this industry is complex due to two remarkable features. First, the market comprises a large number of 117 manufacturers. Second, the most dominant manufacturers belong to corporate groups organized by state-owned enterprise (SOE).[2] On the one hand, the traditional theory (e.g., Tirole [1988]) and empirical findings (e.g., Fraas and Greer [1977], Hay and Kelley [1974]) suggest that collusion is less likely to occur when there is a large number of firms in a market.[3] On the other hand, manufacturers within a corporate group have common stakeholders, large SOE's, which may facilitate tacit collusion since common ownership, similar to cross-ownership, may help with information exchange (Alley [1997]) or reduce the incentive to compete in order to increase the total profits (Reynolds and Snapp [1986]). Furthermore, some firms within corporate groups have multilateral cross-holding investments in each other, which suggests that it is even easier for those firms to set up tacit collusion (Farrell and Shapiro [1990], Gilo *et al.* [2006], Qin, Zhang and Zhu [2010]).[4] Moreover, the Chinese government encourages enterprise alliances and the development of large groups,[5] which reinforces the likelihood of collusion. Hence, the competitive structure of the Chinese automobile industry is indeed unclear.

This paper attempts to clarify how passenger-vehicle manufacturers in China behave and tests whether companies within corporate groups collude in setting price. To conduct the hypothesis test, we estimate the demand and supply functions separately: We first apply the framework of Berry, Levinsohn, and Pakes ([1995], hereafter BLP) to the national sales and car features data of the Chinese passenger-vehicle industry, and estimate the parameters in the demand model. In the second step, we use the estimated demand parameters to calculate the markup under various hypothesized competitive structures, which determines the ownership of car models. The estimated markups are substituted into the pricing equation derived from the first order condition of firms' profit maximization problems. The estimated parameters in the pricing equation, therefore, depend on the hypotheses of market structures.[6] Then, by applying the

[2] See Section II(ii) for details.

[3] While studying a price-setting game with capacity constraints, however, Brock and Scheinkman [1985] found that the likelihood of collusion is not necessarily monotonic in the number of firms. As the number of firms increases, there may come excess capacity, which makes punishment of cheating more severe. It is uncertain whether the large number of firms in the Chinese automotive market actually hinders collusion.

[4] Malueg (1992) suggests that increasing cross-ownership may reduce the likelihood of collusion when firms interact repeatedly. Therefore, it is again inconclusive whether cross-ownership facilitates collusion or not.

[5] See Section II(i) for details.

[6] Goldberg and Verboven [2001] argue that this two-step approach can reduce the computational burden and is flexible in experimenting with different hypotheses about the market structures.

non-nested hypothesis test methodology proposed by Rivers and Vuong [2002], we analyze which hypothesis is supported by our data in the sense that it generates the least pricing-equation residuals statistically.[7] Based on our empirical results, we conclude that no statistical evidence supports within-group collusion in the Chinese passenger vehicle industry. For robustness, we test other assumptions about corporate groups, for example, that they could be led by foreign firms that hold key technologies. However, our findings do not support any form of within-group collusion.

Our study focuses on horizontal collusion in price, assuming no vertical restraints for all the manufacturers. Previous studies show that vertical restraints, such as exclusive dealing or exclusive territory, may or may not lessen competition. Piccolo and Reisinger [2011] show that exclusive territories facilitate tacit collusion between manufacturers in a framework of repeated games. Nurski and Verboven [2012] also find that removing the exclusive dealing will intensify price competition in the European automobile industry. But Asker [2005] finds that exclusive dealing does not reduce competition among brewers in the U.S. beer market. Exclusive dealing does not prevail in the Chinese automobile market, and neither does exclusive territory. For the top five auto dealers in China,[8] for example, most sell more than one brand in an area, while most manufacturers have more than one dealer in a city. Given this fact, we do not investigate the vertical restraints in this paper.

The question of whether collusive behavior exists within passenger vehicle corporate groups is an important area of research because of the impact it could have on future development in the industry. Neglecting to account for collusion could lead to biased results in the study of entry, merger and cost estimation. For example, the Chinese government encourages mergers or collaboration among corporate groups,[9] but a key argument against mergers is that consumers may suffer due to postmerger price increases. However, if collusion exists, then mergers between allied firms would not result in further price increases. Also, the 'merger paradox' suggests that it is more profitable for firms to avoid mergers (Stigler [1950]), but conclusions may change if collusion already exists. So our identification of the market structure may have political implications for the government's plan to develop this industry.

[7] Since we restrict our study to the optimal pricing behavior of an operation, which could be an independent firm or a colluded corporate group depending on collusive hypotheses, the difference in market structure lies in the difference in an operation's ownership matrix. Therefore, our tests about the collusive structure become tests on different assumptions about the ownership matrices. We thank an anonymous reviewer for pointing this out.

[8] The top five dealers ranking by 2011 revenue are China Grand Auto, Pand Da Automobile Trade Co. Ltd., Sinomach Automobile Co. Ltd., Lei Sheng Hang Auto, and Zhongsheng Group.

[9] See Section II(i) for details.

In particular, our results may be of special interest to the policy makers, who are more concerned about the long-term development of indigenous brands. In March, 2009, the State Council of China released the Plan on Adjusting and Revitalizing the Auto Industry, of which two main targets are restructuring the market by merger and enlarging the market shares of indigenous brands. There are many other possible combinations of merger to realize these targets, and the plan was not restricted to the within-group pattern. To illustrate the merger effects based on our findings about the competitive structure, we simulate two merger scenarios and compare the effects of these mergers on the market shares and profits of indigenous brands. Our empirical results show that mergers among firms within corporate groups will expand the market shares of indigenous brands more than mergers among indigenous brands across corporate groups.

This paper is different from previous research in a few ways. First, this paper provides empirical evidence on the relationship between corporate groups and collusion. Most research on this topic targets Japanese corporate groups, bank-centered financial *keiretsu*. Weinstein and Yafeh [1995] found that group-affiliated firms actually compete more fiercely, rather than collude with each other. Alley [1997] applied a conjectural variation model to both Japanese and U.S. automobile industries to compare the degree of collusion in each market, and found collusion exists among auto makers within corporate groups, but he suggested that this is due to the cross-shareholdings between members in a group. Since no conclusive results have been derived, our research attempts to test this relationship. Also, the corporate groups in our study, unlike *keiretsu*, are endogenously organized by some members' parent corporations, which are competitors in the same industry. Their involvement in the cooperation of the subsidiaries and market competition makes the industry structure more ambiguous. On the one hand, membership is not random. Members mutually choose each other, so it is likely that they would cooperate with each other. On the other hand, however, parent companies tend to set up subsidiary joint ventures with firms producing differentiated products, which makes collusion unstable since it is hard to detect deviations. This paper attempts to test whether pricing collusion exists within such corporate groups.

Second, this paper is the first formally to test the market structure of the Chinese automobile industry. Previous studies of this industry have assumed without proof that the market structure exhibits Bertrand Nash competition (Deng and Ma [2010], Xiao and Ju [2011]), neglecting the possible collusion within corporate groups. This might lead to biased estimation of parameters in a structural model if collusion exists (Bresnahan [1987], Ciliberto and Williams [2010]) or poor prediction of structural changes such as merger simulation (Peters [2006]).

Third, we use a unique data set that captures more recent developments. Our data are more consistent with the assumption of utility maximization in consumer behavior, given the fact that most sales come from private households at present. Previous studies, such as Deng and Ma [2010], used historical data before sales of passenger vehicles soared. During their data period, usually before 2001, the major consumption of passenger vehicles came from demand for taxicabs or commercial vehicles. Personal consumption only accounted for 10.9% of the total sales of passenger vehicles in 1995, but rose to 62% in 2002 and jumped further to 89.9% in 2010.[10] Given that the consumption behavior of commercial users is quite different from That of personal consumers, our data on recent sales in the Chinese market from 2004 to 2008 more accurately reflects consumer preferences for passenger vehicles. This is even more important for analyzing the market structure based on demand estimation.

Finally, we use a hypothesis testing methodology that was recently developed by Rivers and Vuong [2002]. By using this method, we can directly identify which structure hypothesis best fits the data. Alley [1997] employed the conjectural variation method, which suffered from the Corts critique [1999]. Weinstein and Yafeh [1995] proposed some hypotheses for testing, but did not actually adopt econometric tools to identify whether a collusion hypothesis better fits the data. We apply the nonnested test method proposed by Rivers and Vuong [2002], because it does not have the problem of the Corts critique and does not require either alternative models to be tested to be correctly specified. This method has been applied in some other empirical work. For example, Bonnet and Dubois [2010] applied it to test the nonlinear pricing structure and vertical relationships between manufacturers and retailers in the French market for bottled water; Bresnahan [1987] used a logically similar method to test whether the price war in 1955 was caused by a change in market structure from collusion to competition.

The rest of the paper is organized as follows: Section II introduces the background on the Chinese passenger-vehicle industry. Section III lays out hypotheses corresponding to various competition structures. Section IV describes the model and econometric analysis method. Section V shows our empirical findings. Section VI summarizes the paper.

II. THE CHINESE PASSENGER-VEHICLE INDUSTRY AND DATA

II(i). *Industrial Policies*

The Chinese automobile industry dates back to the 1950's with the establishment of First Automotive Works (FAW). However, production of passenger vehicles for the mass market did not begin until the early

[10] Data are from State Information Center of China, 2011.

1980's.[11] Since then, demand for passenger vehicles has increased dramatically due to China's economic growth, so much so that the existing firms could not satisfy the demand for either quality or diversity of products. To speed up technological transfer and foreign investment, China's government invited foreign car makers to establish joint ventures with large SOE's.

The National Development and Reform Commission published its Policy on Development of Automotive Industry (PDAI) in 1994, which gave priority to foreign investors with advanced technologies. Attracted by the beneficial policies, most global car makers set up joint ventures in China. In particular after China's acceptance into the World Trade Organization in 2001, the tariff on vehicles declined dramatically to 25% by 2006 and the government dropped its local content requirements.[12] As the number of joint ventures increased further, the industry became more competitive and grew faster than ever. In 2002 and 2003, passenger car production grew by 55.2% and 85.0% respectively, while the number of product models and brands increased from 10 brands and 20 models in 1999 to more than 60 brands and 130 models in 2004. (Holweg, Luo, and Oliver [2009] and China Automotive Industry Yearbook [2005]). In response to the new situation, the PDAI was revised in 2004 to reflect the country's more open trade policies.

This policy, which encourages enterprise alliances and mergers, stated as follows:

> The State encourages development of automobile enterprises groups and forming a new pattern of competition. The country will optimize and upgrade automobile industrial structure by strategic restructuring among enterprises on the basis of market competition in integration with macro control. Strategic restructuring is aimed at supporting automobile production enterprises to organize large groups by asset restructuring, encouraging the founding of enterprises alliances in a co-operation form of complementation of advantages and resources sharing in order to shape up a production pattern of co-ordinated development of large automobile enterprises groups, enterprises alliances and special-purpose vehicle production enterprises. ('Policy on Development of Automotive Industry, 2004', Article 13)

[11] Deng and Ma [2010] record the history of this industry from inception. From the 1950's to early 1980's, Chinese automotive manufacturers mainly produced trucks. The limited supply of passenger vehicles was sold mainly to government officials. Only after China's reform and opening to the world did Chinese auto firms extensively produce passenger vehicles.

[12] This policy requires joint ventures to use 40% of locally made parts and components in their first year of production, and this ratio must increase to 60% and 80% in the second and third years, respectively (Holweg, Luo and Oliver [2009]).

Together with the presence of prevailing corporate groups, this policy may eventually encourage collusion or alliance between manufacturers within corporate groups. In this paper, we focus our analysis on the competitive structure in the industry since this policy took effect.

II(ii). *Major Competitors*

At present, Chinese manufacturers of passenger vehicles can be categorized into two types: indigenous-brand manufacturers, such as BYD, Geely, and Chery, and joint ventures between local manufacturers and foreign car makers such as Shanghai Automotive Industrial Corporation (SAIC) with Volkswagen and General Motors (GM), Beijing Automotive Investment Company (BAIC) with Hyundai, and Dongfeng with Honda.[13] Indigenous-brand manufacturers are usually independent and owned by private companies or local governments, although they may actually imitate the technology of foreign makers (e.g., GM filed a lawsuit against Chery for mini car piracy in 2004) or use some components of the foreign makers (e.g., Holweg, Luo, and Oliver [2009] found that Chery used Volkswagen components). Currently, these indigenous manufacturers have their own research and development (R&D) departments, and their products are mainly low-end small cars. Their market shares are relatively small. Joint ventures, on the other hand, usually belong to corporate groups, centered around SOE's. For instance, SAIC-Volkswagen and SAIC-GM are subsidiaries of The SAIC Group. These corporate groups possess relatively new technologies, so most of their products are medium to high end. Currently, joint ventures dominate this industry, but local brands are expanding rapidly. In 2009, sales from joint ventures accounted for 67.5% of the passenger-vehicle sales in the Chinese market, while indigenous brands accounted for 32.53% of total sales. The market share of local brands increased by 6.6% over 2008.[14] As their sales have expanded rapidly in recent years, they are playing a more significant role in China's market.

Figure 1 shows a rough picture of this industry. Each pair of firms connected by a line constitutes a joint venture, while the independent firms scatter around. Joint ventures in a solid line box belong to one corporate group. Most joint ventures belong to large groups, which are usually independent of each other, although some of them are connected by foreign makers that hold shares in more than one joint venture. Currently, large corporate groups dominate this industry in terms of market share. Table I

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

[14] China Auto Industry Development Annual Report, 2010.

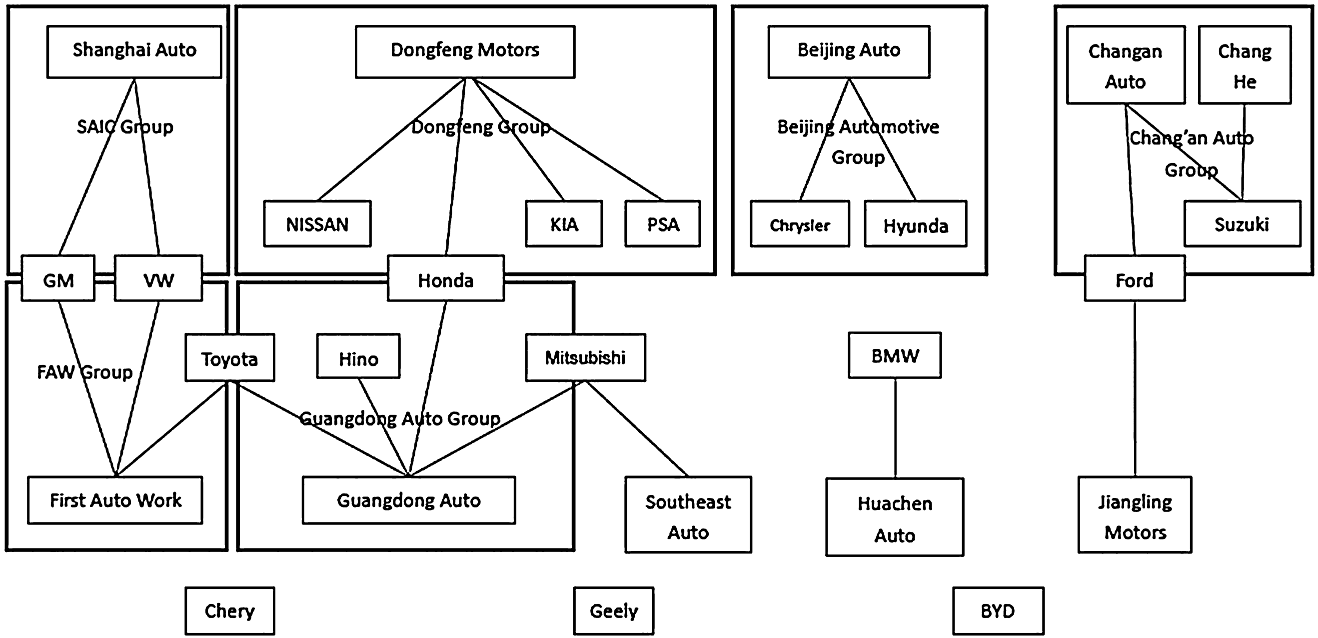

Figure 1
Major Manufacturers in the Chinese Automotive Industry

Notes: Each rectangle with bold border line represents a corporate group, in which are joint ventures between Chinese firms and foreign brands, linked by a line (e.g., Dongfeng-Honda is a joint venture in the Dongfeng Group). The foreign brands on the borders of two corporate groups are those that have joint ventures in both groups (e.g., Honda has two joint ventures: Dongfeng-Honda and Guangzhou-Honda, belonging to Dongfeng Group and Guangdong Auto Group, respectively). Manufacturers, such as Geely and Chery, are independent from big auto groups.

Table I
Top 10 Passenger Vehicle Manufacturers (Group) Based on 2009 Sales

Manufacturers	Sales (units)	Growth Rate (Percent, over 2008)
SAIC-Group	2,705,457	57.23
FAW-Group	1,944,576	26.85
Dongfeng Motor Corporation	1,897,728	43.70
Chang'an Vehicle Group	1,869,802	117.07
Beijing Automotive Industry Holding Co.	1,242,980	61.08
Guangzhou Automotive Group	606,621	15.33
Chery	500,303	40.50
BYD	448,397	162.40
Huachen Automotive Group	348,307	22.11
Geely	329,104	48.36

Source: China Automotive Industry Yearbook 2010.

lists the top 10 manufacturers (groups) by sales. Corporate groups rank higher than the independent indigenous-brand manufacturers BYD, Geely, and Chery.

Corporate groups may facilitate collaboration among members for several reasons. First, the centered SOE holds significant shares in all the members of a group. According to the PDAI, SOE's must hold at least a 50% stake in a joint venture. For their profits, SOE's tend to coordinate among their subsidiaries. Second, some presidents or chief managers of subsidiary companies also hold or have held positions in the parent SOE's or other subsidiaries, which may facilitate information and personnel exchange.[15] Third, there is technology sharing among group members; in particular, the indigenous-brand makers usually adopt technology from one or all joint ventures in the same group. These characteristics may lead the members in a corporate group to behave differently from independent firms. We test whether collusive behavior exists within these groups.

II(iii). *Data*

Data used in this paper come from two sources. The sales data are obtained from the China Association of Automobile Manufacturers (CAAM). CAAM is a nonprofit social organization established in May, 1987. It is a member of the International Organization of Motor Vehicle Manufacturers. CAAM consists of 1,580 member units, including all the major car manufacturers, car parts suppliers and research institutes in China. It collects production and sales data to track the market trends in China and

[15] The concurrent holding of positions is very common for all the corporate groups. Usually, a representative of government holds the chairman' position on the boards of several joint ventures dominated by SOE's within a group. For example, Tianjin FAW Xiali Auto Co., Ltd and FAW Car Co., Ltd, within the FAW group share the same board chairman, as do subsidiaries in the Dongfeng Group.

abroad. Its members report their sales and output information at the product model level every month. An interesting fact is that most entries and exits of car models occurr in January or some month in the second half of the year. In other words, the market structure over half-year intervals is quite stable. We aggregate the monthly data into half years by using the mean of monthly sales.[16] To derive the market shares, we set market size at the number of urban households in China, reported in the fifth national population census by the National Bureau of Statistics in 2000, and assume it to be constant over periods.[17]

Table II reports how representative our data are. Our data cover 76.3% sales on average over 2004–2008. Since sales data include domestic sales and exports, and most exports are small displacement cars, so our data overestimate the domestic market shares for small cars. However, Table II shows that exports only account for 2.98% of passenger-vehicle sales on average. Imported cars and used cars are substitutes for new domestic cars, but they are not included in the sales data. Although the imports only account for 4.8% on average, the sales of used cars is relatively significant, amounting to 18.08% of new car sales. Since we do not have data on either imports or used cars, we treat them as outside goods, together with new car models excluded from our data set and nonpurchase options.

To complement the sales data, we also collect automobile characteristics from a monthly journal, *Car Market Guide* (CMG), which publishes the manufacturer's suggested retail price (MSRP), weight, power, displacement and other information at a more extensive car model level. For instance, CMG distinguishes between automatic and manual transmissions for a model, while CAAM aggregates both statistics for the same car model. Because most cars sold in China have automatic transmissions, we focus on that data category when available. The summary statistics are listed in Table III. The sample size is 1693, which covers most car models sold between January, 2004, and December, 2008.

Our price is the MSRP published by CMG, inflation-adjusted to 2003 prices. Busse *et al.* [2006] suggest that the actual transaction price could be quite different from MSRP due to dealer and consumer promotions, and Hellerstein and Villas-Boas [2010] find that the median transaction prices could be several thousand dollars less than the MSRP on average and exhibit more monthly variation than the MSRP in the U.S. auto market. In the

[16] We do not use the total sales over the half year since observations for some product models are unbalanced due to entry or exit. To make the sales data comparable across models, we use the mean here.

[17] The number of urban households is 84.9 million, 25% of the total number of households in China. Due to the low incomes and limited availability of auto loans in rural areas, most car consumers are urban residents. By the end of 2009, 100 urban households owned 10.89 units of cars, according to the National Bureau of Statistics; the number for rural households was negligible so it was not reported. Therefore, we choose the number of households in cities as the potential market size. Our analysis is not sensitive to this assumption.

TABLE II
TOTAL SALES, IMPORTS, EXPORTS AND USED CAR SALES OVER 2004–2008

		Our data		Imported car		Exported cars		Used passenger vehicle	
Total sales of passenger vehicles (1)		Units (2)	Percentage (2)/(1)	Units (3)	Percentage (3)/(1)	Units (4)	Percentage (4)/(1)	Units (5)	Percentage (5)/(1)
2004	3,068,580	2,295,321	74.80%	162,077	5.28%	73,213	2.39%	482,760	15.73%
2005	3,941,767	3,041,756	77.17%	155,175	3.94%	47,185	1.20%	549,260	13.93%
2006	5,233,132	3,758,421	71.82%	218,624	4.18%	126,344	2.41%	854,079	16.32%
2007	6,381,115	4,862,032	76.19%	302,096	4.73%	264,501	4.15%	13,035,168	20.43%
2008	6,737,745	5,491,020	81.50%	395,799	5.87%	318,593	4.73%	16,159,248	23.98%
mean	5,072,468	3,889,710	76.30%	246,754	4.80%	165,967	2.98%	6,216,103	18.08%

Notes: All the percentages are relative to the total sales of passenger vehicles.

Table III
Summary of Statistics

Variable	Mean	Std.	Min.	Max.
Monthly sales	2271	2686	1	19185
Price (RMB1000)	149.5	110.3	24.19	797.2
Product share	2.68e-05	3.16e-05	1.18e-08	0.000226
Product within-group share	0.00591	0.00736	2.67e-06	0.0717
Efficiency (liters/100 km)	6.903	1.903	3.600	21.70
Weight (1000 kg)	1.341	0.3005	0.645	2.590
Horsepower (kw)	91.44	33.53	26.50	257
Dummy for American cars	0.118	0.322	0	1
Dummy for Japanese cars	0.238	0.426	0	1
Dummy for Korean cars	0.0786	0.269	0	1
Dummy for European cars	0.258	0.438	0	1
Dummy for Chinese cars	0.308	0.462	0	1
Observations		1,693		

Chinese auto market, price promotions sometimes also apply. In particular, we find price discounts are more frequently applied to low-end car models rather than the high-end models,[18] since consumers of high-end models are usually less sensitive to the price. By using the MSRP, therefore, we may have underestimated the consumers' price sensitivity. But given the unavailability of the individual transaction data, we have to follow Deng and Ma [2010] and BLP [1995], using the MSRP to match our aggregate sales.

Car features used in our analysis include fuel consumption, weight, power, and brand information. Fuel consumption is measured by liters of fuel consumed per 100 kilometers. Car models vary widely for this feature: The most efficient car consumes 3.6 liters per 100 km, while the least efficient car uses 21.7 liters per 100 km. Weight is measured by kilograms, and it also demonstrates a large variation over models. Power is measured by kilowatts. The brand dummies indicate the origin of the model's brand. For instance, car models produced by joint ventures with GM, Ford, or Chrysler have brand dummy American as 1, while those produced by joint ventures with Honda or Toyota have brand dummy Japanese as 1. The mean of these brand dummies indicates that American cars account for 11.8%, Japanese cars for 23.8%, and European cars for 25.8% of the total number of car models.

Impressively, Chinese indigenous brands account for 30.8% among all car models produced, with their sales accounting for 26.6% over the sample periods, which shows indigenous brands play a significant role in their domestic market. The top indigenous brands by sales are Chery, Geely and BYD, which are independent of any corporate groups; some indigenous brands, such as Red Flag (product of FAW) and Roewe (product of SAIC),

[18] For high-end models, however, transaction prices could be even higher than the MSRP. For example, consumers had to pay RMB 50,000 more than the MSRP for the base model of Audi Q5 during the early periods when this car was released to the market.

are affiliated with one of the corporate groups. The main difference between the independent and affiliated indigenous brands lies in their relationship with foreign brands. The independent indigenous brands mainly rely on their own R&D for technological innovation, while the affiliated indigenous brands rely more on their foreign partners from the joint ventures in the same corporate group for technology. For example, Roewe vehicles are primarily based on technology acquired from MG Rover. A common feature for these indigenous brands is that most of their car models are low-end products. Their total revenues account for only 15% of the industry revenues, which is close to that of American cars (14.8%) and much lower than that of European cars (27.8 %) and Japanese cars (34.3%).

The common target market makes the indigenous brand products close substitutes, which influences their cooperative intention in two opposite ways: on the one hand, it lowers the probability of cooperation since deviation can enable a player to acquire relatively large market shares from its close substitutes; on the other hand, however, cooperation can greatly increase the price of all close substitutes. In this study, we assume they conduct Bertrand Nash competition in various scenarios. But given the fact that the updated industry policy, PDAI 2009, supports merger between indigenous brands, we simulate a scenario where all the indigenous brands cooperate in pricing decisions. Such cooperation is possible since the indigenous brands are solely owned by the Chinese firms. We make a comparative static analysis and present the equilibrium prices and market shares of the indigenous brands. Our results may be of special interest to the policy makers, who are more concerned about the long-term development of indigenous brands.

III. FACTS AND HYPOTHESES

Article 48 of the 2004 industrial policy explicitly stipulates that Chinese participants in a joint venture with foreign makers must own at least 50% of the company's shares; a foreign firm can form joint ventures with only two Chinese companies and may invest in a third firm as a party of a joint venture. Therefore, Chinese firms retain at least equal decision power as their foreign partners in most of the joint ventures. This generates the possibility that joint ventures within corporate groups with SOE's as a parent company may collude.[19] Also, as pointed out in the last section, the

[19] As a stakeholder of SOE's, the Chinese government could also organize a collusion among all the joint ventures in which SOE's hold dominant stakes. However, this does not actually happen. Some SOE's are owned by municipal governments, which have considerable autonomy and pursue their tax income in their respective region. Even if the SOE's are owned by the central government, the local government still has significant influence on them through supporting policies. Therefore, SOE's are actually fragmented and it is hard for different SOE's to collude.

chief personnel arrangement and technology exchange among members may also lead to collusion. Hence, motivated by these industry policies and facts, we make our first hypothesis about the competition structure as,

Hypothesis 1 (H1). Manufacturers within corporate groups centered around a common SOE collude to maximize their joint profits.

However, the SOE in a group may not be a powerful organizer because foreign makers actually control the subsidiary joint ventures in three ways. First, they have the key technology or control over the research and development department.[20] The initial reason for Chinese SOE's to cooperate with foreign makers was to exchange markets for technology, but technology transfer did not happen to any significant extent: Because joint ventures dominated the Chinese market, they were able to operate with large profits even while they postponed the update of products (Holweg, Luo and Oliver [2009]). Since joint ventures must rely on foreign partners for technology, this gives foreign partners significant bargaining power in the joint venture. Second, the key parts of cars are usually produced by foreign makers or a joint venture controlled by foreign makers. Examples include FAW-Volkswagen Engine Co., Ltd. (FAW 40%, Volkswagen 60%) and Guangzhou Toyota Engine Co. Ltd. (Guangzhou Automotive 30%, Toyota Investment (China) 12.4%, and Toyota 57.6%). Holweg, Luo, and Oliver [2009] found that approximately 1,700 automotive component suppliers had been registered in China, of which about 450 were partially or fully foreign owned. Moreover, these joint ventures of international suppliers possess advanced production technology and R&D capabilities, therefore they actually lead in the components market. Third, foreign managers usually occupy the most important positions in a joint venture (e.g., the presidents of Guangzhou Toyota and Honda both are Japanese, although neither of them has a dominant stake in the respective joint venture). Therefore, there is a possibility that foreign makers may eventually break down the SOE-centered corporate groups and form their own collusive groups to maximize their profits.

Hypothesis 2 (H2). Joint ventures with common foreign makers eventually form corporate groups, centered around these foreign makers, and collude.

Corporate groups have some overlaps via some foreign makers, such as Volkswagen, GM (FAW Groups and SAIC groups), and Honda (Dongfeng Group and Guangdong Auto Group). If these foreign makers

[20] For example, Pan Asia Technical Automobile Center Co., Ltd., the first Sino-foreign automotive engineering and design joint-venture between General Motors and Shanghai Automotive Company (SAC) in China, provides technical support to Shanghai GM. Although GM and SAC each have 50% shares , the president and the core technical teams are American engineers.

have enough power in their respective groups, then corporate groups with common foreign investors may have incentives to collude for the sake of firms' direct and indirect financial interests. Therefore, another possible collusive scenario is,

Hypothesis 3 (H3). Collusion happens between companies belonging to groups with common foreign investors, i.e., the foreign makers.

As a benchmark, our final hypothesis assumes that collusion does not exist, and members in corporate groups seek profit maximization autonomously:

Hypothesis 4 (H4). No collusion exists. Joint ventures conduct Bertrand Nash competition to maximize their respective profits.

To make our analysis complete, we also test two other hypotheses. One breaks the firms into smaller decision-making units, and another assumes all corporate groups collude. Since the main purpose of this paper is to investigate whether firms within corporate groups behave differently than independent firms, we do not list these extreme cases here but instead present them in the Appendix.

IV. EMPIRICAL MODEL AND HYPOTHESIS TEST METHOD

IV(i). *Model*

Demand. In our analysis of consumer behavior, we use a random-coefficient nested logit model. The random-coefficient model imposes few restrictions on own and cross-price elasticities since it allows heterogeneity in the sensitivity of individuals to product prices. All automobiles in our sample set are placed in a single nest and separated from outside goods since consumers' preferences for products in the same market could be correlated but different from preferences for outside goods, which are quite different from our sample products (see data section for details).

The indirect utility of consumer i from purchasing product j at market t is

$$\begin{aligned} u_{ijt} = \beta_0 - \alpha_i \ln p_{jt} + \beta_{iE} Efficiency_j + \beta_{iW} Weight_j + \beta_{iH} Horsepower_j \\ + \beta_{iA} Amr_j + \beta_{iJ} Jap_j + \beta_{iK} Kor_j + \beta_{iE} Eur_j + \xi_j + \zeta_{ig} + \rho\varepsilon_{ijt}, \end{aligned}$$

where p_{jt} is the price of product j at market t; $Efficiency_j$ measures the fuel consumption. $Weight_j$ is the product weight, and $Horsepower_j$ indicates the power. Amr_j, Jap_j, Kor_j, Eur_j, are binary variables indicating the area of origin associated with the model's brand. Since Japanese and Korean cars have reputations for fuel efficiency, they are close substitutes to the indigenous cars; thus, we specify their country of origin. We categorize all brands into five groups with origins from Japan ($Jap_j = 1$), Korea ($Kor_j = 1$), Europe ($Eur_j = 1$), America ($Amr_j = 1$), and China (all the binary variables equal to zero). These variables are usually regarded as the main factors affecting car choice. Our specification of observable characteristics is similar to literatures about the U.S. car market (e.g., BLP [1995], Train and Winston [2007]) and European car market (e.g., Goldberg and Verboven [2001]). The difference is we do not employ car size as they do; therefore, we use weight as an independent measurement of comfortability, rather than using it to normalize the horsepower as the above literatures did. Hence, it will not be surprising to get a positive estimate for this variable. BLP [1995] also includes a dummy variable for air-conditioner, which only accounts for 11.6% among car models between the 1970's and 1990's. We do not use this variable since an air-conditioner has been a standard equipment in most car models since. Another frequently used variable in studies of the automobile market is displacement. We found that it is highly correlated to power, so we did not include it in the demand model.

In the equation, ξ_j are unobserved product characteristics, which may also influence consumer utility; ξ_{jg} is a nested logit random taste that is constant across automobile products and differentiates transportation by automobiles from the ' outside' good. ρ is the nested logit parameter, which approaches one when the within-group correlation of utility levels goes to one and approaches zero when the within-group correlation goes to zero. ε_{ijt} is the consumer-specific deviation from the mean utility, and α, β_0, β_{iE}, β_{iW}, β_{iH}, β_{iC}, and ρ are demand parameters to be estimated. We further assume that coefficients of price and product characteristics depend on individuals' idiosyncratic tastes and could be decomposed into two parts: the average preference, α or β, and idiosyncratic preference, μv_i, where μ measures variation in consumers' tastes and v_i is consumer's idiosyncratic taste, following log-normal distribution for price coefficient and normal distribution for coefficients of other characteristics, respectively; therefore, the coefficients for price and product characteristics could be written as, $\alpha_i = \alpha + \mu v_i$ and $\beta_i = \beta + \mu v_i$, respectively.

If we use $\mathbf{x}$ to denote the vector of product characteristics, and θ to denote the vector of parameters on the demand side, then Berry [1994] shows that the market share of product j is a function of product price, $\mathbf{p}$, unobservable characteristics $\boldsymbol{\xi}$, observable characteristics $\mathbf{x}^d$, and function parameters θ, as follows:

$$(1) \qquad s_{jt}\left(\mathbf{p}, \mathbf{x}^d, \boldsymbol{\xi}, \theta\right) = \int \frac{e^{\delta_{ijt}/(1-\rho)}}{\left(\sum_k e^{\delta_{ikt}/(1-\rho)}\right)^{\rho}\left(1+\left(\sum_k e^{\delta_{ikt}/(1-\rho)}\right)^{1-\rho}\right)} dv_i$$

where $\delta_{ijt} = \mathbf{x}_t^d \theta_i + \xi_j$ is the mean utility of product j for individual i. Here, the aggregate market share for product j at market t is the integration of the individual market share over the distribution of the idiosyncratic taste distribution.

Supply. On the supply side, we use *operation* to name the price-setting unit. It could be a manufacturer competing with others independently or a corporate group consisting of manufacturers. In various scenarios, operation is a profit maximizer. It coordinates pricing decisions on all the products under its control,

$$\max_{\{p_{jt}\}_{j\in\mathcal{F}_f}} \sum_{j\in\mathcal{F}_f} p_{jt} M s_{jt}\left(\mathbf{p}, \mathbf{x}^d, \boldsymbol{\xi}, \theta\right) - C_j\left(\mathbf{x}_j^s, \omega_j, \gamma\right),$$

where $\mathcal{F}_f$ denotes the set of car models produced by operation f. M is the market size, which is exogenous to our model. $C_j\left(\mathbf{x}_j^s, \omega_j, \gamma\right)$ is the total cost. The corresponding marginal cost is denoted by $c_j\left(\mathbf{x}_j^s, \omega_j, \gamma\right)$, where γ is a vector of unknown parameters, and $\mathbf{x}_j^s$ and ω_j are the vectors of observed cost components and unobserved cost components, respectively. We specify the marginal cost function for product j as follows:

$$\begin{aligned} \ln c_j = {} & \gamma_0 + \gamma_E \mathit{Efficiency}_j + \gamma_W \mathit{Weight}_j + \gamma_H \mathit{Horsepower}_j \\ & + \gamma_A \mathit{Amr}_j + \gamma_J \mathit{Jap}_j + \gamma_K \mathit{Kor}_j + \gamma_E \mathit{Eur}_j + \omega_j, \end{aligned} \tag{2}$$

where c_j is the marginal cost for product j, which is assumed to be invariant over time. The other independent variables are defined the same as on the demand side; γs, are unknown cost parameters to be estimated.

In equilibrium, the optimal prices of operation f satisfy the following first-order conditions:

$$\begin{aligned} 0 = {} & s_{jt}\left(\mathbf{p}, \mathbf{x}^d, \boldsymbol{\xi}, \theta\right) + \left[p_{jt} - c_j\left(\mathbf{x}_j^s, \omega_j, \gamma\right)\right] \frac{\partial s_{jt}\left(\mathbf{p}, \mathbf{x}^d, \boldsymbol{\xi}, \theta\right)}{\partial p_{jt}} \\ & + \sum_{r\neq j, r\in\mathcal{F}_f} \left[p_{rt} - c_r\left(\mathbf{x}_r^s, \omega_r, \gamma\right)\right] \frac{\partial s_{rt}\left(\mathbf{p}, \mathbf{x}^d, \boldsymbol{\xi}, \theta\right)}{\partial p_{jt}} \end{aligned}$$

Or, in the form of vectors, the first-order condition can be written as

$$\mathbf{p} = \mathbf{c} - \left(D_p \mathbf{s}.*\mathbf{I}\right)^{-1}\mathbf{s}, \tag{3}$$

where

$$D_p\mathbf{s} = \begin{bmatrix} \frac{\partial s_1}{\partial p_1} & \cdots & \frac{\partial s_N}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial p_N} & \cdots & \frac{\partial s_N}{\partial p_N} \end{bmatrix},$$

and **I** is the ownership/coordination matrix with

$$(4) \qquad I_{jr} = \begin{cases} 1, & \text{if } j \in \mathcal{F}_f \text{ and } r \in \mathcal{F}_f \\ 0, & \text{otherwise,} \end{cases}$$

where .* stands for entry-by-entry multiplication instead of the usual matrix multiplication.

Here, $-(D_p\mathbf{s}.{*}\mathbf{I})^{-1}\mathbf{s}$ in equation (3) is the difference between the MSRP and marginal costs of manufacturers; therefore, it is the sum of the retail and manufacturer price-cost margins. Given that MSRP is set by the manufacturer, and it is competitive on the retailer side, we assume the retailers' margins account for the same portion of the total price-cost margins across all brands, which implies that the price-cost margins are determined by the competition structure on the manufacturer side. From the equilibrium price equation (3) and cost function (2), we can derive an identifiable equation as follows,

$$(5) \qquad \ln\left(\mathbf{p} + (D_p\mathbf{s}(\mathbf{p}).*\mathbf{I})^{-1}\mathbf{s}(\mathbf{p})\right) = \mathbf{x}^s\gamma + \omega_j$$

Equation (5) shows that the difference in price-cost margins over different scenarios stem from the ownership matrix (4). Therefore, to test the alternative hypotheses about the competition structure actually is to examine which assumption of the ownership matrix makes the observed cost variables best fit the estimated marginal costs.

IV(ii). *Estimation*

We estimate the parameters on the demand side and supply side in sequence. In this way, we ignore the correlation between the demand and cost functions and assume consistent consumer behavior in various scenarios.[21] Because parameters on the demand side describe consumers' preference over product features, which embodies the nature of underlying market demand over our sample period, it is reasonable to assume demand to be consistent under various scenarios, and indeed it is standard in the literature (e.g., Bonnet and Dubois [2010], Goldberg and Verboven [2001], Villas-Boas [2007]). After estimating the parameters θ on the demand side, we plug the fitted value $\hat{\theta}$ into the left-hand side of equation (5) and then estimate the cost-side parameters γ using the method of generalized least squares.

For the demand-side estimation, the procedure follows BLP methodology using the generalized method of moments (GMM). One problem with

[21] We also estimated the parameters on both sides jointly. The results are quite similar to the ones presented here, except for the scenario of all-firm collusion.

the demand estimation lies in the aggregation of individual product choice probability into the market level since we only have data on aggregate market share rather than individual purchase records. To derive aggregate market share in equation (1), we need to know the idiosyncratic consumer preference v_i, which is actually unobservable. Since it follows log normal distribution, we use a simulation method to make n random draws from its distribution and calculate the individual purchase probability for each product.[22] Finally, we calculate the aggregate market shares using a numerical method as follows:

$$\tilde{s}_{jt}\left(\mathbf{p}, \mathbf{x}^d, \boldsymbol{\xi}, \theta\right) = \frac{1}{n}\sum_{v_i} \frac{e^{\delta_{ijt}/(1-\rho)}}{\left(\sum_k e^{\delta_{ikt}/(1-\rho)}\right)^{\rho}\left(1+\left(\sum_k e^{\delta_{ikt}/(1-\rho)}\right)^{1-\rho}\right)} \tag{6}$$

We use contraction mapping and a direct search algorithm to estimate the demand parameters, by matching equation (6) to observed market shares. Specifically, for each set of starting values of $\tilde{\rho}$, and the parameter of idiosyncratic tastes, $\tilde{\mu}$, we use contraction mapping to find a vector of product mean utility, $\tilde{\delta}_{ijt}(\tilde{\rho}, \tilde{\mu})$, minimizing the distance between the predicted market share $\tilde{s}_{jt}$ and the observed market share. Then, the difference between mean utility and the product of observable product characteristics and their associated parameters generates the unobservable characteristic, ξ_j. Using the fact that ξ_j is independent of some exogenous variables, we can construct the moment conditions. By searching over $\tilde{\rho}$ and $\tilde{\mu}$ using Nelder-Mead simplex algorithm, we can find the optimal solution minimizing the moment conditions.

Since the unobservable characteristics in our model are correlated with price, another problem with the demand estimation is the endogeneity problem. To solve this problem, we choose instrumental variables (IV) as specified in the next subsection. We assume one set of instrumental variables, z^d, to be mean independent of unobserved product characteristics, ξ, in equation (1). Then, the demand estimator will satisfy

$$E\left[\xi_j(\theta) \middle| z^d\right] = 0,$$

or

$$E[m(\theta)] = 0,$$

where, $m(\theta) = (\delta_j - x^d\theta^d)z^d$. The corresponding sample moment condition is given by,

[22] In this study, we set $n = 2000$.

$$(7) \qquad \hat{G}(\theta) = \frac{1}{n}\sum\left(\delta_j - x^d\theta^d\right)z^d = 0$$

Asymptotically, we choose the estimator that minimizes the weighted sum of the squared moment conditions (7). Following BLP, we use an inverse matrix of instrumental variables as the weighting matrix in the GMM estimation.

Knittel and Metaxoglou [2012] point out that different starting values and tolerance values for the fixed-point iterations may lead to convergence at multiple local minima for the random-coefficient discrete choice model. To guarantee the robustness of our demand estimates, we try 50 different pseudo-random starting values drawn from the standard normal distribution and choose a tight tolerance for the change in the parameter vector, 1E-10. We employed the Nelder-Mead simplex searching algorithm without using analytical gradients since Knittel and Metaxoglou [2012] suggest that the other search algorithm with analytical gradient does not necessarily generate more consistent estimates.

IV(iii). *Instruments*

The first set of demand IV's is own and rivals' exogenous product attributes. The instruments along this line include exogenous product characteristics (including efficiency, weight, horsepower, and country dummy variables that indicate the origin of the models' brand), the corresponding sum of the exogenous characteristics (including efficiency, weight, and horsepower) of the other products by the same operation, and the corresponding sum of the exogenous characteristics (including efficiency, weight, and horsepower) over products of the other operations. The second set of demand IV's includes the squares of the first set of IV's, following Train and Winston [2007]. The validity of these instruments stems from the assumption that the observed product characteristics are independent of the unobservable characteristics, and the fact implied by the first-order condition equation (3) that own and rival products have different effects on the product markup. We use the first and second order sum of characteristics of own and rival products to approximate the nonlinear function of these characteristics in the first order conditions. All these IV's will affect pricing decisions, so they are correlated with price, but they are independent of the error terms since they are exogenous to the demand side; hence, they are valid instrumental variables.

The third set of demand IV's includes the interaction of steel price with the first set of IV's and the interaction of labor cost in the transportation manufacturing sector with the first set of IV's. Given the fact that about

50% of steel inputs for car production in 2003 were imported,[23] we use the export price index for iron and steel mill products from the U.S. Bureau of Labor Statistics to measure the steel price. We use these factor price indices as cost shifters to show the efficiency of the first two sets of IV's.[24]

IV(iv). *Identification*

The number of demand parameters is determined by the dimension of product characteristics in the indirect utility function. Given the endogeneity problem for the price and within-group market share, we need at least two more exogenous variables excluded from the demand side to identify the demand parameters, using the moment condition (7). As discussed in Section IV(iii), our IV's are valid to construct two extra moment conditions to identify the demand parameters. Since we use the sum and its squares of the characteristics over own and rival products, we actually have more moment equations than parameters; so demand parameters are overidentified. We apply GMM estimation to handle the overidentification problem using the weighting described in Section IV(ii).

Using the estimates on the demand side, we can estimate the price-cost margin and thus the marginal costs in equation (5) under each hypothesis of the market structure. Since marginal costs are correlated with the product characteristics, by estimating the correlation between the estimated marginal costs and product characteristics we can identify which hypothesis regarding the market structure fits the cost estimates best.

IV(v). *Nonnested Tests for Market Structure*

We use the Rivers and Vuong [2002] method to test hypotheses proposed in the previous section (see Appendix for details). Intuitively, different hypotheses correspond to different assumptions on the ownership matrices (4). For example, the ownership matrices are an identity matrix for single product competition and a matrix with each element equal to 1 for full collusion. When we estimate equation (5), it will generate various residuals for different ownership matrices. We compare the residuals for each pair of hypotheses and construct statistics using the ratios of the residuals. We reject the null hypothesis except when the residuals from a null hypothesis are significantly smaller than those from an alternative hypothesis. We perform the pairwise tests on any two of the hypotheses since the test results are not transitive.

[23] *Report on China Automobile Steel Market 2003–2005*, by Great Wall Securities Co. Ltd., [2003].

[24] We thank an anonymous reviewer for suggestions about this issue.

Here is the procedure for a general nonnested test when a GMM estimation is used. Suppose there are two alternative models, M_1 and M_2, for each pair of competitive structures for comparison. To estimate the model parameters, the moment conditions that we use for M_1 and M_2 are, respectively,

$$E[m_1(\theta_1)] = 0$$

$$E[m_2(\theta_2)] = 0,$$

where both moment equations share the same set of instruments, z.

After deriving the estimates, $\hat{\theta}_i$, for both models, we construct a test statistic, $T_n = \frac{\sqrt{n}}{\hat{\sigma}}\left(\hat{Q}_1 - \hat{Q}_2\right)$, which follows standard normal distribution (Rivers and Vuong [2002], Hall and Pelletier [2011]). $\hat{Q}_1$ and $\hat{Q}_2$ are the values of the first-step objective functions that employ the same consistent estimator of the weighting matrix W, defined as $W = \frac{1}{n} z'z$. The objective function value, $\hat{Q}_i$ is defined as $\hat{Q}_i = \hat{G}_i' W \hat{G}_i$, where $\hat{G}_i = \frac{1}{n}\sum m_i\left(\hat{\theta}_i\right)$. $\hat{\sigma}^2$ is the sampling variance of the difference between objective functions given as,

$$\hat{\sigma}^2 = 4[G_1' W E_{11} W G_1 + G_2' W E_{22} W G_2 - 2G_1' W E_{12} W G_2],$$

where, $\hat{E}_{ij} = \frac{1}{n}\sum m_i\left(\hat{\theta}_i\right) m_j\left(\hat{\theta}_j\right)'$.

In a hypothesis test, the null hypothesis (H_0) is that M_1 and M_2 are asymptotically equivalent; the first alternative hypothesis (H_1) is that M_1 is asymptotically better than M_2; the second alternative hypothesis (H_2) is that M_2 is asymptotically better than M_1. Let a denote the desired (asymptotic) significance of the test and $z_{a/2}$ the corresponding critical value from standard normal distribution. If $T_n < -z_{a/2}$, we reject H_0 in favor of H_1; if $T_n > z_{a/2}$, we reject H_0 in favor of H_2; Otherwise, we do not reject H_0.

V. EMPIRICAL RESULTS

V(i). *Parameter Estimation*

Demand side. All the estimates from different starting values point to two local minima in our study. We choose the one generating the less functional value.

Table IV displays the estimates of demand parameters. We first report the results of the logit model, assuming away the nested group. The price coefficient is positive and insignificant, due to the endogeneity problem; also the coefficients for both weight and horsepower are counterintuitive: Consumers will prefer large and powerful cars, while our results show the opposite preference.

TABLE IV
DEMAND ESTIMATION (1)

	Logit OLS	Nested Logit OLS	Nested Logit with IV	Random coefficients nested logit
Explanatory variable				
Nest-coefficient ρ	—	0.9557***	0.7728***	0.7566***
	—	(221.0164)	(24.7797)	(22.9518)
Mean level of the coefficient on ln(price)	0.1730	–0.3982***	–0.8461***	–0.9176***
	(1.1746)	(–13.6812)	(–7.7509)	(–6.0311)
Standard deviation of the coefficient on ln(price)	—	—	—	0.2631***
	—	—	—	(2.6728)
Efficiency	–0.0551**	–0.0049	–0.0134**	–0.0189***
	(–2.4472)	(–0.9904)	(–2.0011)	(–2.6706)
Weight	–0.6184***	0.2043***	0.4589***	0.4238***
	(–2.8317)	(4.4791)	(4.3588)	(3.7381)
Horsepower	–0.0090***	0.0049***	0.0077***	0.0059***
	(–3.7285)	(10.5498)	(5.1411)	(3.8150)
Dummy for American cars	0.4892***	0.0907***	0.3283***	0.3162***
	(4.0969)	(3.9439)	(8.5683)	(8.0139)
Dummy for Japanese cars	0.4885***	0.1265***	0.3775***	0.3644***
	(4.7141)	(6.3364)	(10.6317)	(9.9161)
Dummy for Korean cars	0.2077	0.0746***	0.2117***	0.2160***
	(1.3897)	(3.0942)	(5.0773)	(4.8388)
Dummy for European cars	–0.0318	0.1675***	0.4115***	0.3634***
	(–0.2513)	(7.4717)	(6.7604)	(5.7819)
Dummy for the first half year	—	—	—	—
	—	—	—	—
Constant	–10.2762***	–4.4778***	–4.1243***	–4.0435***
	(–24.3780)	(–51.1174)	(–9.9389)	(–9.0123)
Observations	1693	1693	1693	1693
R2	0.1008	0.9700	0.9278	—
First stage F-stat: ln(conditional market share)	—	—	21.35	
First stage F-stat: ln(price)	—	—	589.47	589.47

Note: t-statistics are in parentheses. *, **, and *** indicate 10%, 5% and 1% significance level.
Coefficient on ln(price) is assumed to follow the log normal distribution.
Demand and supply are estimated in sequence.

Results of nested logit are shown in the second column. Now, most of the estimates are of the expected sign, although the estimate of efficiency is insignificant. The estimate of within-group correlation of utilities, ρ, is 0.96, which means the consumers perceive the products in our data set as close substitutes relative to the outside goods. Comparing the R_2 between the nested logit and the logit model, we find the fitness of the nested logit model improved by a large magnitude, which indicates that consumers perceive the outside goods quite differently from the products in our data, and neglecting this difference will lower the prediction efficiency.

We present the results of the IV nested logit model. Here, we use the first two sets of IV's to solve the endogeneity problem in the price and the conditional market share. The use of IV's generates substantial changes in several of the estimates. The price coefficient is more than double that in the nested logit model. Such a result indicates that the price coefficient will be overestimated (underestimated in magnitude) if we do not take into account the endogeneity problem: Products with superior quality usually sell at higher prices, so the price is positively correlated with the unobservable characteristics, which generates a positive biased estimator. The coefficient of efficiency now is significant and almost two times larger. The coefficients of weight and horsepower are also much larger than those in the nested logit model. The F-statistics show that the IV's are valid: They are highly correlated with the endogenous variables. Hereafter, we use the same IV's for the estimation of random coefficient models unless noted otherwise.

Finally, we present the results of the random coefficient nested logit model in the last column of Table IV. All the estimates are consistent with our intuition. The coefficient for price is negative and significant. For a Chinese-brand car with features at mean level, the price elasticity corresponding to this price coefficient is -3.03. The standard deviation of consumers' idiosyncratic tastes on price is 0.26, which is relatively small compared to the mean level, implying consumers are not quite heterogeneous in their price sensitivity. Consumers prefer cars with large size, high power, and low fuel consumption. Also, consumers prefer foreign brands to indigenous ones; in particular, European cars are most popular in China's market. The within group coefficient is 0.76, close to one, which indicates consumers' utility over car models is highly correlated.

We also try other combinations of independent and instrumental variables and report the results in Table V. First, we add a first-half year dummy to the model. Its estimate is insignificant, and the other estimates do not change much, except that the coefficients for price and the standard deviation on price are less efficient. Second, we include the standard deviations of the distribution of marginal utilities for all the key product features into the model. However, the results show that all the estimates of these standard deviations are insignificant; again, the other estimates do not

TABLE V
DEMAND ESTIMATION (2)

Explanatory variable	Random coefficients nested logit (1) Means	Random coefficients nested logit (1) Standard Deviations	Random coefficients nested logit (2) Means	Random coefficients nested logit (2) Standard Deviations	Random coefficients nested logit with cost IV Means	Random coefficients nested logit with cost IV Standard Deviations
Nest-coefficient ρ	0.7408***	—	0.7499***	—	0.7388***	
	(23.5839)	—	(21.4385)	—	(24.0999)	
ln(price)	−0.8780***	0.3060*	−0.8700***	0.2541	−0.7886***	0.2701*
	(−3.4975)	(1.7209)	(−3.9909)	(1.4637)	(−5.0977)	(1.8147)
Efficiency	−0.0200***	—	−0.0248***	0.0003	−0.0191***	
	(−2.6538)	—	(−2.0211)	(0.0012)	(−2.6101)	
Weight	0.3701***	—	0.4164	−0.0800	0.3391***	
	(3.2713)	—	(1.1847)	(−0.0696)	(3.1844)	
Horsepower	0.0051***	—	0.0057***	0.0002	0.0050***	
	(3.3651)	—	(3.1691)	(0.0218)	(3.1905)	
Dummy for American cars	0.3068***	—	0.3111***	—	0.2985***	
	(7.5583)	—	(7.5465)	—	(7.4276)	
Dummy for Japanese cars	0.3526***	—	0.3591***	—	0.3425***	
	(9.3794)	—	(8.6245)	—	(9.1600)	
Dummy for Korean cars	0.2073***	—	0.2086***	—	0.1979***	
	(4.4272)	—	(4.5252)	—	(4.3335)	
Dummy for European cars	0.3324***	—	0.3520***	—	0.3182***	
	(5.3541)	—	(5.3234)	—	(5.1815)	
Dummy for first half of a year	0.0176	—	—	—		
	(0.5555)	—	—	—		
Constant	−4.2380***	—	−4.1745***	0.1000	−4.4432***	
	(−6.9772)	—	(−7.8172)	(0.0337)	(−10.0618)	
Observations	1693		1693		1693	
First stage F-stat: ln(price)	589.47		589.47		571.68	

Note: t-statistics are in parentheses. *, **, and *** indicate 10%, 5% and 1% significance level. Coefficient on ln(*price*) is assumed to follow the log normal distribution. Demand and supply are estimated in sequence.

Table VI
Summary of Elasticity Estimates

Elasticities	
Own-price elasticities	
Mean	–3.051***
	(–179.8)
25% quantile	–3.212***
	(–110.9)
Median	–3.031***
	(–171.7)
75% quantile	–2.846***
	(–133.3)
Cross-price elasticities	
Mean	0.009***
	(180.4)
25% quantile	0.001***
	(8.919)
Median	0.004***
	(9.386)
75% quantile	0.012***
	(15.02)

Note: *** indicates 1% significance level

change significantly. Finally, we use the third set of IV's and report the results in the last two columns of Table V. This set of IV's consists of the cost shifters, such as the steel price and employee wages, and their interaction with the product characteristics. They are supposed to be valid IV's since they are correlated with price but uncorrelated with the unobservable product characteristics. Our results show that all the estimates are quite similar to those in the last column of Table VI, except that the magnitude of price coefficient is a little bit smaller (-0.79). Such a result also proves the validity of the first two sets of traditional IV's. For the following sections, therefore, we will use the results of the random coefficient nested logit model with first two sets of IVs as shown in the last column of Table VI.

Implications of the elasticity. Before looking into the results from formal hypothesis tests, we present the price elasticity of demand based on the demand estimation. The random coefficient nested logit model allows more general substitution patterns between the products, since consumers are assumed to have idiosyncratic preference over the price; so our results are free from the independence of irrelevant alternatives property of standard logit models. Table VI summarizes the product-level elasticities. Given the fact that these elasticities depend on the estimates of model parameters, we use a bootstrap method with 500 replications to calculate the test statistics. Basically, the rough picture of the distribution of elasticities shows us that our results are similar to those in Goldberg and Verboven [2001]; in particular, the cross-price elasticities are in the same order of magnitude.

We display the firm-level elasticities for the top ten firms (without considering their possible within-group collusion) in Table VII. The rows of

TABLE VII
OWN AND CROSS PRICE ELASTICITIES OF TOP 10 CHINESE AUTO MANUFACTURERS

	Beijing Hyundai	Guangzhou Honda	Shanghai GM	Shanghai VW	Chang'an Ford & Mazda	Dongfeng	First Auto VW	Chery	Geely	BYD
Beijing Hyundai	−2.911***	0.141**	0.166***	0.183***	0.065**	0.158***	0.274***	0.134***	0.075**	0.111***
	(−44.791)	(2.396)	(3.818)	(4.053)	(2.318)	(2.939)	(4.148)	(3.491)	(2.080)	(3.077)
Guangzhou Honda	0.104***	−2.703***	0.163***	0.176***	0.064**	0.154***	0.274***	0.111***	0.063*	0.094***
	(3.928)	(−26.164)	(3.765)	(3.919)	(2.318)	(2.871)	(4.119)	(3.014)	(1.872)	(2.734)
Shanghai GM	0.106***	0.141**	−2.748***	0.179***	0.065**	0.155***	0.274***	0.120***	0.068**	0.101***
	(4.071)	(2.442)	(−29.701)	(4.022)	(2.337)	(2.911)	(4.121)	(3.440)	(2.041)	(2.986)
Shanghai VW	0.108***	0.141**	0.165***	−2.789***	0.065**	0.156***	0.274***	0.127***	0.072**	0.106***
	(4.074)	(2.407)	(3.811)	(−43.300)	(2.322)	(2.918)	(4.142)	(3.534)	(2.081)	(3.038)
Chang'an Ford & Mazda	0.105***	0.142**	0.164***	0.178***	−2.807**	0.155***	0.274***	0.114***	0.065*	0.097***
	(4.020)	(2.435)	(3.783)	(3.977)	(−28.528)	(2.892)	(4.084)	(3.203)	(1.956)	(2.879)
Dongfeng Motor Corporation	0.107***	0.141**	0.165***	0.180***	0.065**	−2.775***	0.274***	0.122***	0.069**	0.102***
	(4.076)	(2.436)	(3.808)	(4.016)	(2.325)	(−32.496)	(4.115)	(3.433)	(2.116)	(3.054)
First Auto-VW	0.104***	0.141**	0.163***	0.176***	0.064**	0.154***	−2.587***	0.113***	0.064**	0.096***
	(4.134)	(2.488)**	(3.793)	(4.020)	(2.365)	(2.926)	(−23.966)	(3.649)	(2.217)	(3.202)
Chery	0.120***	0.135**	0.168***	0.193***	0.063**	0.162***	0.268***	−3.211***	0.106**	0.157***
	(4.076)	(2.240)	(3.799)	(4.121)	(2.217)	(3.020)	(4.162)	(−35.008)	(2.100)	(3.214)
Geely	0.120***	0.137**	0.169***	0.194***	0.064**	0.162***	0.270***	0.187***	−3.262***	0.151***
	(3.995)	(2.243)	(3.811)	(4.080)	(2.223)	(3.018)	(4.204)	(3.349)	(−34.224)	(2.935)
BYD	0.119***	0.136**	0.168***	0.193***	0.064**	0.162***	0.269***	0.187***	0.101**	−3.208***
	(4.085)	(2.255)	(3.848)	(4.118)	(2.235)	(3.016)	(4.167)	(3.513)	(2.060)	(−22.768)

Note: The i th row and j th column stand for the percentage change of total market shares of the i th auto group when the prices of the j th auto group change by 1%. *, **, and *** indicate 10%, 5% and 1% significance level, respectively.

the table correspond to the percentage changes in market share of the firms with respect to 1% price changes for all the models of firms listed in the column. Self-elasticities vary from -2.61 to -3.30 over firms, which indicates that every firm faces a price-sensitive demand. But cross-elasticities vary to a large degree across firms. Due to their extensive product mix, when Shanghai GM and VW lower their prices by 1%, the other top manufacturers will lose about 0.17% or 0.18 % market shares each; in contrast, for Chang'an-Ford or Mazda, decreases in their prices will result in trivial market share loss for the others (about 0.05% or 0.017%, respectively). Overall, the magnitude of cross-elasticity is much less than that of self-elasticity; therefore, none of the firm pairs produces very close substitutes, so firms have price-setting power and are less likely to coordinate their pricing decisions (Chang [1991]). On the other hand, even if firms coordinate their prices, defection is tempting since a 1% reduction in price will bring forth a significant increase in demand obtained from all the other firms, while the market share of any individual competitor will not decrease much so that it is not easy to detect such a defection. For instance, when Shanghai GM or VW reduce their price by 1%, they will acquire about 1.69% or 1.85% market shares, respectively, from the other top nine manufacturers; but this price cut will only result in a maximum individual market share loss of 0.27% for First Auto VW. Our analysis implies that collusion between firms, if any, is not stable.

Supply side. Supply side estimates depend on the assumption about competition structure, so we display the results corresponding to each hypothesized market structure in the first four columns of Table VIII. Actually, the estimates under various hypotheses are quite similar. We can draw some common conclusions from the estimates under the rest of the hypotheses: First, preferable car features are costly. Coefficients for both weight and horsepower are positive and significant, which means comfortable and powerful cars cost more in production. Second, the marginal costs of all foreign brand cars are higher than those of local brands. This could be because foreign car makers invest more on unobservable product quality features other than weight and horsepower.

We leave discussion of price-cost margins to the next section, to focus on the estimates of the supported model. But note that the price-cost margins are quite similar over various hypotheses, ranging from 33.7% to 36.3%.

V(ii). *Hypothesis Tests*

We test our hypotheses more formally and present results in Table IX. Each column corresponds to a null model, while each row corresponds to an alternative model. The test statistics in the table follow standard normal distribution. When the test statistics are significantly small (lower than the

Table VIII
Supply Estimation

Hypothesis	Within-Group Collusion (H1)	Foreign Firm Collusion (H2)	Cross-Group Collusion (H3)	Bertrand Competition (H4)	Single product Competition (H5)	All Firms Collusion (H6)
Explanatory variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Efficiency	0.002	0.002	0.001	0.002	0.002	—
	(0.473)	(0.409)	(0.285)	(0.543)	(0.437)	—
Weight	0.695***	0.695***	0.697***	0.695***	0.687***	—
	(14.766)	(14.610)	(14.717)	(14.701)	(14.487)	—
Horsepower	0.009***	0.009***	0.009***	0.009***	0.009***	—
	(20.932)	(20.871)	(21.078)	(20.741)	(20.683)	—
Dummy for American cars	0.219***	0.233***	0.201***	0.247***	0.268***	—
	(10.920)	(11.433)	(9.974)	(12.259)	(13.286)	—
Dummy for Japanese cars	0.290***	0.279***	0.276***	0.293***	0.302***	—
	(15.440)	(14.731)	(14.629)	(15.550)	(15.969)	—
Dummy for Korean cars	0.180***	0.174***	0.177***	0.178***	0.185***	—
	(9.286)	(8.870)	(9.034)	(9.166)	(9.560)	—
Dummy for European cars	0.434***	0.411***	0.393***	0.448***	0.469***	—
	(23.161)	(21.691)	(20.557)	(23.983)	(25.165)	—
% positive costs	1.000	1.000	1.000	1.000	1.000	0.1790
Cost, c	93.544	93.416	92.380	94.409	96.040	—
Markup, $p-c$	55.984	56.112	57.148	55.119	53.489	182.752
Markup rate, $\frac{p-c}{p}$	0.354	0.355	0.363	0.348	0.337	1.6286
Observations	1693					

Note: t-statistics are in parentheses. Demand and supply are estimated in sequence.
*, **, and *** indicate 10%, 5% and 1% significance level, respectively.
Within-group collusion (H1)—joint ventures with common dominant stakeholder, SOE, are assumed to collude.
Foreign-firm collusion (H2)—joint ventures with common foreign firms are assumed to collude.
Cross-group collusion (H3)—corporate groups linked by common foreign firms are assumed to collude.
Bertrand Nash competition (H4)—firms are assumed to compete without collusion.
Single product competition (H5)—product model is the unit of pricing decision.
All firms collusion (H6)—all firms collude and behave like monopolists.

TABLE IX
NONNESTED TESTS ON MARKET STRUCTURE

Null hypothesis / Alternative hypothesis	Within-Group Collusion (H1)	Foreign Firm Collusion (H2)	Cross-Group Collusion (H3)	Bertrand Competition (H4)
Foreign Firm Collusion (H2)	1.453			
Cross-group Collusion (H3)	–1.791	–2.869		
Bertrand Nash competition (H4)	3.020	1.822	2.544	
Single Product Competition (H5)	0.346	–0.290	0.975	–2.474

Note: Tabele shows test statistics of the null model in a row being true against the specified alternative model in a column. The test statistics follow standard normal distribution.

one-tail critical value -1.64, at 5% significance), this means the residuals under the null model could not be explained by the alternative model, thus the null model is asymptotically better than the alternative. When the test statistics are significantly large (higher than the one-tail critical value 1.64, at 5% significance), then the alternative model is asymptotically better than the null. Otherwise, they are asymptotically equivalent.

We can draw two main conclusions from our results. First, our data support H4, that manufacturers conduct Bertrand Nash competition, coinciding with our intuition from the elasticity estimation. The model corresponding to H4 generated significantly smaller residuals than all the others, so the t-statistics show that we can reject all null hypotheses at the 5% significance level when the alternative is H4. We conclude that joint ventures are autonomous in price setting. Given that hypotheses about within-group collusion or collusion through foreign firms (H1 and H2) are rejected, this result implies all partners in a joint venture target the firm's maximum profit without considering their respective brands' other subsidiaries in China.

Furthermore, this result indicates that the core firm of a group, the SOE, cannot organize collusion among members, even though it holds dominant (or at least 50%) shares in the firm. Since most members of corporate groups are joint ventures of the SOE and other global brands, this means foreign brands have more bargaining power than the SOE and choose not to collude with the other joint ventures within the group. Their advantage comes from owning advanced technology. Due to the lack of R&D investment,[25] most Chinese manufacturers have to rely on their foreign partners for continuous technology transfer. Therefore, even if foreign firms only hold minor shares in a joint venture, they have strong power to make strategic decisions such as pricing.

[25] The Chinese auto industry annual report [2010] shows that R&D expenditures by the Chinese auto industry was US$5.67 billion, accounting for 2.07 % of annual revenue, while the American auto industry spent 3.9% of annual revenue on R&D.

Second, collusion across groups (H3) is rejected by alternative hypotheses H2 and H4. The Chinese passenger vehicle market is fragmented, and corporate groups located in different places are supported by their respective local governments. So, it is not a surprise to see that collusion among these groups is not supported by our data, even though some of them share the same foreign investors (see Figure 1). Actually, when these investors choose their partners, they may use one partner to bargain with the others, which increases competition between groups.

The average price-cost margin for the unrejected model is 34.8%, as shown in Table VIII. This is consistent with our elasticity estimations but a bit higher than the estimates for the same industry by Deng and Ma [2010]. This is due to the difference in sampling frequency. Our sales are monthly averages over half years, while Deng and Ma [2010] used annual observations. For a longer observation period, data usually exhibit more variation in both prices and sales, so the elasticities are higher and the margins are lower due to the relationship to elasticity indicated by the Lerner index. Given this margin is the gross margin, without taking into account the fixed cost, which usually takes a nontrivial share of revenues for the auto industry, our results are reasonable.

V(iii). *Counterfactual Analysis*

The Bertrand Nash competition spreads capital and other resources thinly and thereby hinders the development of large-scale automobile plants capable of competing with foreign makers (Holweg, Luo and Oliver [2009]). In 2009, only five Chinese auto manufacturers produced more than one million vehicles, with only one firm (SAIC) producing more than two million; in contrast, most globally competitive manufacturers produced more than one million (e.g., Toyota produced 7.2 million, GM produced 6.4 million, and Volkswagen produced 6.1 million).

The Chinese government supports merger and acquisition among auto works.[26] In March, 2009, the General Office of the State Council released the ‘Plan on Adjusting and Revitalizing the Auto Industry,’ (hereafter, the Plan), of which two main targets were to restructure the market by merger and to enlarge the market shares of indigenous brands. For the first target, this plan explicitly states: ‘through merger, acquisition, and reorganization, form 2 or 3 large auto enterprise groups with a scale of production and sale exceeding 2 million vehicles and 4 or 5 auto enterprise groups with a scale of production and sale volume exceeding 1 million vehicles.’ To give an impetus to the reorganization in the auto industry, ‘the state encourages the

[26] Fershtman and Pakes [2000] shows that collusive industry offers more variety and higher quality goods, which improves consumer surplus more than loss due to higher prices. This may justify the government’s policy.

nation-wide merger, acquisition and reorganization activities of the FAW Group Corporation, Dong Feng Motor Corporation, Shanghai Automotive Industry Corporation (Group), Changan Auto Co. Ltd. and other large auto enterprises, supports the regional merger, acquisition and reorganization activities of Beijing Automobile Works Co., Ltd., Guangzhou Automobile Industry Group Co., Ltd., Chery Automobile Co., Ltd., China National Heavy Duty Truck Group Corp., Ltd. and other auto enterprises.' Obviously, this policy supports within-group merger and acquisition. Since some indigenous brands belong to some corporate groups while the others are independent, the within-group mergers have ambiguous effects on the indigenous brands; in particular, the effect on their total market share, which is the second target of the Plan , is unclear. We simulate this scenario and analyze comparative statics for the indigenous brands. In the short run, these mergers will not lower the marginal costs, but only internalize the competition between brands. Therefore, the effect of mergers would be similar to that of collusive price setting described by our H1.

Moreover, the Plan does not restrict mergers to the within-group pattern. There are many other possible combinations of mergers that could to realize these two targets. For example, the low-end indigenous manufacturers, such as Chery, BYD, and Geely, could merge to alleviate competition in the same target market. Their status of independent innovation and development make such mergers possible. We simulate another scenario of indigenous brand merger and compare it to the first scenario in terms of the average price, market share, and profit of each interest group.

The simulation results of within-group mergers are shown in Table X. The postmerger average price increased by 1.1%, but the market-level total sales decreased by 1.02% due to the higher prices. This coincides with merger theory, which says merged manufacturers control output and charge higher prices. Mergers made the profit of the industry increase by 2.72%, with a 3.12% firm-level increase. We further explain these results by investigating the comparative statics for each interest group.

In this counterfactual experiment, we assumed that corporate-group members, which are usually joint ventures, merge; therefore, it is not a surprise to see that both indigenous and foreign brands in the joint ventures charge a higher price postmerger (by 2.4% and 1.38% respectively). The total market share decreased by 2.64% for the foreign-brand models, while that of the indigenous brands did not change significantly, so we observe that the profit of indigenous brands produced by joint ventures increased by 3.04%. The profit of foreign brands also increased by 2.63% since the price increase was large enough to compensate for the market share loss of the foreign brands. Since prices are often strategic complements, it is reasonable to see that individual manufacturers also increased their prices by a very small scale, 0.1%, on average. The overall asymmetric price increase

TABLE X
COMPARATIVE STATISTICS FOR VARIOUS INTEREST GROUPS (WITHIN-GROUP MERGER)

	Pre	$\widehat{\text{Post}}$	$\frac{\widehat{\text{Post}}-\text{pre}}{\text{pre}}$	Pre	$\widehat{\text{Post}}$	$\frac{\widehat{\text{Post}}-\text{pre}}{\text{pre}}$
	All models			Models of indigenous brands, produced by individual Chinese firms		
Product average						
Price, p	132.098	133.505***	0.011***	68.851	68.880***	0.001***
		(20.453)	(4.404)		(21.510)	(3.583)
Firm-level average						
Market share, s	0.000141	0.000139***	0.0116**	0.000103	0.000106***	0.0322***
		(9.921)	(2.058)		(5.133)	(3.830)
Conditional market share, s_{jg}	0.0250	0.0250***	0.0220***	0.0183	0.0191***	0.0428***
		(27.914)	(2.736)		(6.107)	(3.889)
Profit (RMB1000)	5.198×10^5	5.339×10^5***	0.0312***	1.705×10^5	1.761×10^5***	0.0333***
		(9.438)	(4.100)		(4.869)	(4.007)
Market-level total						
Market share, s	0.00563	0.00557***	–0.0102***	0.00155	0.00160***	0.0300***
		(11.034)	(–4.168)		(5.343)	(3.720)
Conditional market share, s_{jg}	1	1	0	0.275	0.286***	0.0405***
					(6.359)	(3.811)
Profit (RMB1000)	2.079×10^7	2.136×10^7***	0.0272***	2.557×10^6	2.642×10^6***	0.0332***
		(10.324)	(4.326)		(5.010)	(4.012)

Table X Continued

	Models of foreign brands, produced by joint ventures			Models of indigenous brands, produced by joint ventures		
Product average						
Price, p	167.054	168.898***	0.0138***	96.240	99.551***	0.024***
		(18.616)	(4.237)		(10.130)	(2.939)
Firm-level average						
Market share, s	0.000174	0.000169***	0.00861	0.0000526	0.0000521***	–0.0507***
		(6.820)	(1.593)		(2.895)	(–2.838)
Conditional market share, s_{jg}	0.0308	0.0303***	0.0190**	0.00934	0.00934***	–0.0410**
		(10.963)	(2.451)		(3.089)	(–2.224)
Profit (RMB1000)	8.083×10^5	8.295×10^5***	0.0302***	9.046×10^4	9.321×10^4**	0.0285***
		(7.527)	(4.164)		(2.080)	(3.703)
Market-level total						
Market share, s	0.00382	0.00372***	–0.0264***	0.000263	0.000260***	–0.0103
		(7.750)	(–4.634)		(2.614)	(–0.354)
Conditional market share, s_{jg}	0.678	0.667***	–0.0164***	0.0467	0.0467***	–0.0000884
		(14.22)	(–4.228)		(2.789)	(–0.00304)
Profit (RMB1000)	1.778×10^7	1.825×10^7***	0.0263***	4.523×10^5	4.660×10^5**	0.0304***
		(8.559)	(4.303)		(1.837)	(3.909)

Note: Within corporate-group merger is applied to all firms.
*, **, and *** indicate 10%, 5% and 1% significance level, respectively.

and merged-firm output control switched consumer demand to the individual manufacturers outside of corporate groups, whose market share increased by 3%. Since joint ventures mainly produce high-end car models and individual manufacturers focus on small cars, saved demand on the joint venture side should lead to more purchases for individual manufacturers; however, we observe a decrease of overall market shares (−1.02%). This result reflects that high-end and low-end demand are not substitutable.

Changes in market shares for different interest groups show that this merger pattern will help indigenous brands such as Geely and Chery acquire market shares (conditional on purchase) from the foreign brands. Therefore, such a merger within a corporate group will eventually contribute to the realization of the Plan's target for indigenous brands' market shares.

Table XI displays the simulation results for merger among indigenous brands. In this experiment, we assume that all the indigenous brands, no matter whether they belong to a corporate group or are independent manufacturers, merge, leaving the competitive relationship unchanged for the joint ventures. The average product price increased significantly for all the indigenous brands (13.4% for independent firms and 11.1% for joint ventures), while the price of foreign-brand products decreased by a tiny scale, 0.42%. Accordingly, the market shares of indigenous brands decreased by 27.6% and 29.7% for independent firms and joint ventures, respectively. Some of the consumers switched to foreign brands, whose market shares then increased by 9.17%, while some consumers chose the outside goods; this caused the total market share to decrease by 2.77%. Therefore, such a merger pattern contradicts the second target of the Plan since it lowers the market shares of indigenous brands.

VI. CONCLUDING REMARKS

This paper investigates some feasible collusive scenarios in the Chinese passenger-vehicle industry. Our empirical findings support the assumption of Bertrand Nash competition in the market. However, other forms of coordination may exist that lie outside of the scope of the models we have tested. For example, in this study we assume that collusive patterns are generally applied to all the corporate groups, but partial collusion is also possible, which would not be replicable among all the other groups. To analyze partial collusion, we need to test hypotheses about various combinations of partial collusion. Given that the number of corporate groups is large, however, the number of feasible patterns in partial collusion is too large to be analyzed one-by-one. However, our method allows a partial-collusion analysis that could be used in future case studies of actual mergers.

TABLE XI
COMPARATIVE STATISTICS FOR VARIOUS INTEREST GROUPS (INDIGENOUS-BRAND MERGER)

	Pre	$\widehat{\text{Post}}$	$\frac{\widehat{\text{Post}}-\text{pre}}{\text{pre}}$	Pre	$\widehat{\text{Post}}$	$\frac{\widehat{\text{Post}}-\text{pre}}{\text{pre}}$
	All models			Models of indigenous brands, produced by individual Chinese firms		
Product average						
Price, p	132.098	134.605	0.0462	68.851	76.635***	0.134
		(21.180)***	(4.805)***		(22.061)	(5.663)
Firm-level average						
Market share, s	0.000141	0.000137***	–0.0754***	0.000103	0.0000748***	–0.293***
		(9.790)	(–6.053)		(5.486)	(–8.916)
Conditional market share, s_{jg}	0.0250	0.0250***	–0.0490***	0.0183	0.0137***	–0.272***
		(27.914)	(–3.460)		(6.515)	(–9.148)
Profit (RMB1000)	5.198×10^5	5.562×10^5***	0.0614***	1.705×10^5	1.787×10^5***	0.0348***
		(10.015)	(4.046)		(4.687)	(3.114)
Market-level total						
Market share, s	0.0056	0.0055***	–0.0277***	0.0015	0.0011***	–0.276***
		(10.881)	(–4.166)		(5.760)	(–9.686)
Conditional market share, s_{jg}	1	1	0	0.275	0.205***	–0.256***
					(6.852)	(–10.250)
Profit (RMB1000)	2.079×10^7	2.225×10^7***	0.070***	2.557×10^6	2.680×10^6***	0.0482***
		(11.009)	(4.223)		(4.814)	(4.603)

TABLE XI Continued

	Models of foreign brands, produced by joint ventures			Models of indigenous brands, produced by joint ventures		
Product average						
Price,p	167.054	166.352*** (18.487)	−0.0042*** (−4.347)	96.240	104.157*** (11.342)	0.111*** (6.195)
Firm-level average						
Market share, s	0.000174	0.000190*** (7.794)	0.104*** (4.235)	0.0000526	0.0000370** (2.486)	−0.193*** (−6.112)
Conditional market share, s_{jg}	0.0308	0.0346 (15.042)	0.135*** (4.136)	0.0093	0.0068*** (2.665)	−0.170*** (−5.797)
Profit (RMB1000)	8.083×10^5	8.678×10^5*** (8.218)	0.0818*** (4.038)	9.046×10^4	9.493×10^4** (2.038)	0.0544*** (3.985)
Market-level total						
Market share, s	0.0038	0.0042*** (9.063)	0.0917*** (4.050)	0.000263	0.00185** (2.264)	−0.297*** (−8.183)
Conditional market share, s_{jg}	0.678	0.761*** (25.493)	0.123*** (3.995)	0.0467	0.033** (2.414)	−0.277*** (−8.091)
Profit (RMB1000)	1.778×10^7	1.909×10^7*** (9.481)	0.0736*** (4.014)	4.523×10^5	4.747×10^5* (1.797)	0.0495*** (3.402)

Note: Indigenous brand merger is applied to all firms..
*, **, and *** indicate 10%, 5% and 1% significance level, respectively.

Our counterfactual experiment suggests that China's merger stimulus policy will benefit the independent indigenous brands rather than large joint ventures in market acquisition. But mergers among indigenous brands will make indigenous brands lose market share. However, since the technology in the automobile industry usually exhibits economy of scale, the marginal cost is likely to decrease by a larger scale for large firms, enabling them to lower prices and grab market share from the unmerged firms. In particular, since the indigenous brands produce close substitutes, they may better enjoy economies of scale from mergers with other independent indigenous firms. Taking this into account may affect our conclusions about these two patterns of merger and is a challenge for future research.

APPENDIX

(i). *Other Hypotheses and Empirical Results*

For robustness, we also test two extreme cases: single product line pricing and monopolistic pricing. The first case assumes that every product model is managed independently: This hypothesis actually assumes the market to be in perfect competition at the product line level. The second case, on the other hand, assumes that all manufacturers make pricing decisions collusively, so they effectively form a cartel. These two scenarios can be summarized as Hypotheses 5 and 6,

Hypothesis 5 (H5): Each product line is operated by an independent manager, who maximizes the profit of the single product.

Hypothesis 6 (H6): All manufacturers in this industry form a cartel and make pricing decisions collusively.

We test these hypotheses using the same method described in Section IV(v). Parameter estimates corresponding to hypotheses 5 and 6 are appended to Table VIII. Most estimates are quite similar to those of Hypotheses 1–4, with the exception of those of H6. However, only 18.67 % of car models carry a positive marginal cost under H6, so this hypothesis is rejected safely at this stage and the corresponding estimates are not reported. Note that the estimated average marginal cost is also significantly lower than those under other hypotheses, which generates an unbelievable markup rate, 162%. The normal markup rates for the other cases are about 35%, which is much more reasonable.

Results of hypothesis tests are reported in Table IX. First, H5 is rejected when the alternative hypothesis is H4, so our data do not support the hypothesis of perfect competition either.

Finally, the monopoly hypothesis (H6) is rejected by all the other alternative hypotheses.[27] This indicates the competitive feature of this market from another aspect: Any more competitive hypothesis generates smaller regression residuals.

[27] Results are not reported in Table IX but are available upon request.

REFERENCES

Alley, W., 1997, 'Partial Ownership Arrangement and Collusion in the Automobile Industry', *The Journal of Industrial Economics*, 45(2), pp. 191–205.

Asker, J., 2005, 'Diagnosing Foreclosure Due to Exclusive Dealing', New York University working paper,(New York Universits, New York, New York, U.S.A.)

Berry, S., 1994, 'Estimating Discrete Choice Models of Product Differentiation,' *RAND Journal of Economics*, 25, pp. 242–262.

Berry, S.; Levinsohn, J. and Pakes, A., 1995, 'Automobile Prices in Market Equilibrium,' *Econometrica*, 60(4), pp. 889–917.

Bonnet, C. and Dubois, P., 2010, 'Inference on Vertical Contracts between Manufacturers and Retailers Allowing for Nonlinear Pricing and Resale Price Maintenance,' *RAND Journal of Economics*, 41(1), pp. 139–164.

Bresnahan, T. F., 1987, 'Competition and Collusion in the American Automobile Industry: The 1955 Price War,' *The Journal of Industrial Economics*, 35(4), pp. 457–482.

Brock, W. and Scheinkman J., 1985, 'Price Setting Supergames with Capacity Constraints,' *Review of Economics Studies*, 52, pp. 371–382.

Busse, M.; Silva-Risso, J., and Zettelmeyer, F., 2006, '$1,000 Cash Back: The Pass-Through of Auto Manufacturer Promotions,' *American Economic Review*, 96(4), pp. 1253–1270.

Chang, M., 1991, 'The Effects of Product Differentiation on Collusive Pricing,' *International Journal of Industrial Organization*, 9, pp. 453–469.

China Automotive Research Center, 2006, '*China Automotive Industry Yearbook 2005*'. (The Center, Beijing China).

Ciliberto, F. and Williams, J., 2010, 'Does Multimarket Contact Facilitate Tacit Collusion? Inference on Conjectural Parameters in the Airline Industry,' *SSRN working paper*.

Corts, K., 1999, 'Conduct Parameters and the Measurement of Market Power,' *Journal of Econometrics*, 88, pp. 227–250.

Deng, H. and Ma, A., 2010, 'Market Structure and Pricing Strategy of China's Automobile Industry,' *Journal of Industrial Economics*, 58(4), pp. 818–845.

Farrell, J. and Shapiro, C., 1990, 'Horizontal Mergers: An Equilibrium Analysis,' *American Economic Review*, 80(1), pp. 107–26.

Fershtman, C. and Pakes, A., 2000, 'A Dynamic Oligopoly with Collusion and Price Wars,' *RAND Journal of Economics*, 31(2), pp. 207–236.

Fraas, A. and Greer, D., 1977, 'Market Structure and Price Collusion: An Empirical Analysis,' *The Journal of Industrial Economics*, 26(1), pp. 21–44.

Gilo, D.; Moshe, Y. and Spiegel, Y., 2006, 'Partial Cross Ownership and Tacit Collusion,' *RAND Journal of Economics*, 37(1), pp.81–99.

Goldberg, P. K. and Verboven, F., 2001, 'The Evolution of Price Dispersion in the European Car Market,' *Review of Economic Studies*, 68(4), pp. 811–848.

Hall, A. R. and Pelletier, D., 2011, 'Nonnested Testing in Models Estimated via Generalized Method of Moments,' *Econometric Theory*, 27(2), pp. 443–456.

Hay, G. and Kelley, D., 1974, 'An Empirical Survey of Price Fixing Conspiracies,' *Journal of Law and Economics*, 17(1), pp. 13–38.

Hellerstein, R. and Villas-Boas, S. B., 2010, 'Outsourcing and Pass-Through,' *Journal of International Economics*, 81(2), pp.170–183.

Holweg, M.; Luo, J. and Oliver, N., 2009, 'The Past, Present and Future of China's Automotive Industry: A Value Chain Perspective,' *International Journal of Technological Learning, Innovation and Development*, 2(1–2), pp. 76–118.

Knittel, C. and Metaxoglou, K., 2012, 'Estimation of Random Coefficient Demand Models: Challenges, Difficulties and Warnings,' MIT working papers (Massachusetts, Instituted Technology, Cambridge, Massachusetts, U.S.A.)

Malueg, D., 1992, 'Collusive Behavior and Partial Ownership of Rivals,' *International Journal of Industrial Organization*, 10(1), pp. 27–34.

Nurski, L. and Verboven, F., 2012, 'Exclusive Dealing as a Barrier to Entry? Evidence from Automobiles,' SSRN working paper, Available from SSRN: *http://ssrn.com/abstract=1984562* or *http://dx.doi.org/10.2139/ssrn.1984562*

Peters, C., 2006, 'Evaluating the Performance of Merger Simulation: Evidence from the U.S. Airline Industry', *Journal of Law and Economics*, 49, pp. 627–649.

Piccolo, S. and Reisinger, M., 2011, 'Exclusive Territories and Manufacturers' Collusion', *Management Science*, 57(7), pp. 1250–1266.

Qin, C.; Zhang, S. and Zhu, D., 2010, 'Cross-Holdings in Oligopoly: Pairwise Stability and Anti-Competitiveness,' University of California at Santa Barbara, Economics working paper series (Department of Economics, University of Califomia at Santa Barbara, Santa Barbara, Califomia, U.S.A.)

Reynolds, R. and Snapp, B., 1986, 'The Competitive Effects of Partial Equity Interests and Joint Ventures,' *International Journal of Industrial Organization*, 4(2), pp. 141–153.

Rivers, D. and Vuong, Q., 2002, 'Model Selection Tests for Nonlinear Dynamic Models', *Econometrics Journal*, 5, pp. 1–39.

Stigler, G., 1950, 'Monopoly and Oligopoly by Merger,' *The American Economic Review, Papers and Proceedings*, 40(2), pp. 23–34.

Tirole, J., 1988, *The Theory of Industrial Organization* (MIT Press, Cambridge, Massachusetts, U.S.A.).

Train, K. E. and Winston, C., 2007, 'Vehicle Choice Behavior and the Declining Market Share of U.S. Automakers,' *International Economic Review*, 48(4), pp. 1469–1496.

Villas-Boas, S. B., 2007, 'Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data,' *The Review of Economics Studies*, 74 (2), pp. 625–652.

Wang, H., 2003, 'Policy Reforms and Foreign Direct Investment: The Case of the Chinese Automobile Industry,' *Journal of Economics and Business*, 6(1), pp. 287–314.

Weinstein, D. and Yafeh, Y., 1995, 'Japan's Corporate Groups: Collusive or Competitive? An Empirical Investigation of Keiretsu Behavior,' *The Journal of Industrial Economics*, 43(4), pp. 359–376.

Xiao, J. and Ju, H., 2011, 'Market Equilibrium and the Environmental Effect of Tax Adjustments in China's Automobile Industry,' Fudan University working paper. (Fudan university, Yangpu, Shanghai, China).