Local Protectionism, Market Structure, and Social Welfare: China's Automobile Market

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Abstract

While China has made great strides in transforming its centrally-planned economy to a market-oriented economy, there still exist widespread interregional trade barriers, such as policies and practices that protect local firms against competition from non-local firms. This study documents the presence of local protectionism and quantifies its impacts on market competition and social welfare in the context of China's automobile market, the largest automobile market in the world. Using a census of vehicle registration records, we show that joint ventures (JVs) and especially state-owned enterprises (SOEs) command much higher market shares in their headquarter province than at the national level. Results from a spatial regression discontinuity analysis at provincial borders and falsification tests suggest that this pattern is not driven by differences in consumer preference or dealer network, and point to local protectionism such as subsidies of local brands as the primary contributing factor. We then set up and estimate a market equilibrium model to quantify the impact of local protectionism, controlling for other demand and supply factors. Our counterfactual simulations show that local protectionism leads to significant choice distortions and consumer welfare loss. It also benefits JVs and SOEs at the expense of more efficient private firms. In the long run, local protectionism could have important impacts on market structure such as firm entry and exit as well as resource allocation across regions.

Keywords: Local Protectionism, Regression Discontinuity, Market Equilibrium Model, Welfare

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1 Introduction

Since the implementation of market reform and open-up policy in 1978, China has made great strides in transforming its centrally-planned economy to a market-oriented economy. By recognizing private ownership, unleashing entrepreneurial spirit, and promoting international trade, the reform has led to a phenomenal economic growth with an annual GDP growth rate of 10 percent for over 35 years.[1] Despite the tremendous progress made in integrating with the world economy, China's domestic market still exhibits widespread interregional barriers to trade. One such barrier includes policies and practices that protect local firms against competition from non-local firms, which we characterize as local protectionism. Local protectionism manifested in these trade barriers arises from a combination of factors: the top-down political personnel system that relies heavily on local GDP growth for promotion, rent-seeking behaviour of local officials, and the lack of effective regulations from the central government.

Distortionary polices and practices that affect factor allocation in the *input* market are documented in both developed and especially developing countries (Banerjee and Munshi, 2004; Peek and Rosengren, 2005; Hsieh and Klenow, 2009). Studies have shown that these policies and practices could have substantial effects on productivity and aggregate output (Baily et al., 1992; Restuccia and Rogerson, 2008; Brandt et al., 2009). Our study documents the presence of local protectionism and quantifies its impacts on market competition and social welfare in an *output* market, the automobile market in China. Discriminatory policies and practices imposed by local governments change the relative prices of products based on their origin of production. This in turn distorts consumer choices, affects how resource and production are allocated across automakers, and has long-term impacts on market structure and economic performance. Recent policy discussions, in the midst of slowing Chinese economy, have focused on strengthening domestic demand to promote future economic growth. Understanding the impact of local protectionism (and interregional trade barriers in general) on market competition and social welfare could have important implications for future policies.

Using a census of registration records at the individual vehicle level from 2009 to 2011, we document that vehicle models produced by state-owned enterprises (SOEs) and joint ventures (JVs) command a much higher market share in their headquarter province than at the national level, a phenomenon that we call 'home bias'. We first present evidence that home bias survives controls for consumer demographics, distance and transportation costs, dealer networks, and a variety of geographic and temporal fixed effects. To test whether the home bias is driven by consumer preference, we employ a spatial regression discontinuity design by focusing on the clusters of adjacent

[1] This process was unfolded in three major waves: the reform in the agricultural sector that started in 1978 and made farmers residual claimants, the privatization of State-own Enterprises (SOEs) from the late 1980's, and the entry to WTO in 2001, respectively.

counties on different sides of provincial borders. We show that strong home bias persists within these county clusters: even though counties within a cluster have similar culture, customs, consumer demographics and access to dealer stores, SOE and JV products command much higher market shares in counties located in their headquarter province than in the adjacent counties across the province border. In contrast, home bias is *absent* for models produced by private automakers, a pattern that is robust across various specifications. A consumer survey of recent Chinese car buyers shows that few consumers can distinguish between private or SOE products. These results suggest that the home bias we have documented is not chiefly driven by either consumer demographics or consumer ethnocentrism (such as pride and voluntary support for local products), since we control for the former by focusing on clusters of similar counties, and the later would have led to a similar home market advantage by the private firms. Our falsification tests show that non-local products that are most similar in attributes to local SOE or JV products do not enjoy any sales advantage in local products' home market. In addition, there is no systematic differences in consumer preference in adjacent counties across the borders of non-producing provinces (provinces that do not have any auto firms). Together these results suggest that local protective policies and practices instead of consumer preference heterogeneity are the key driver behind our finding. While it is impossible to obtain an exhaustive list of such policies, we have uncovered a series of them that are targeted toward SOE and JV products (see section 2 for more details).

To understand the impacts of local protectionism on market competition and social welfare, we set up and estimate a market equilibrium model in the spirit of Berry et al. (1995), incorporating local protectionism as a price subsidy on local products. Demand parameters are estimated using provincial-level sales data (macro-moments) and a household survey of new vehicle buyers (micro-moments). First, the estimation results suggest that local protectionism (including explicit subsidies and implicit barriers) is equivalent to a price discount of 28% for SOE products and 11% for JV products, which leads to a sales increase of about 277.1% for SOEs and 44.5% for JVs in their headquarter province. Second, estimated subsidies and other preferential treatment amount to 34 billion Yuan from 2009 to 2011. Counterfactual simulations show that choice distortions induced by local protectionism lead to a consumer welfare loss of 12.3 billion Yuan (nearly $2 billon) during the three years of our sample, while industry profit and tax revenue increase by 8 billion Yuan due to the subsidies. In addition, these policies lead to substantial redistribution: they benefit affluent car buyers at the expense of less wealthy consumers and benefit high-cost SOEs and JVs at the expense of more efficient private automakers. Note that our estimates are conservative: they do not take into consideration the additional social cost that is associated with collecting taxes to finance these subsidies, exclude institutional purchase (cars procured by local governments and taxi companies, etc.) that is subjected to local protection, omit subsidies that auto firms receive during the production process (subsidy on capital and R&D, tax exemptions, etc.), and ignore long-term consequences of local protection. The aggregate welfare loss associated with local protection in the passenger car sector of the auto industry could be much bigger than the one presented here.

Our study makes the following three contributions to the literature. First, it adds to the literature on understanding brand preferences and market share dynamics. Bronnenberg et al. (2012) show that brand preferences based on past experience are highly persistent and can explain a large percent of geographic variation in market shares. Schmalensee (1982) and Sutton (1991) examine market share dynamics in the temporal dimension and illustrate that early entrants can gain a persistent competitive edge through consumer learning and advertising.

In the automobile market, the most closely related papers include Goldberg and Verboven (2011) and Cosar et al. (2016). The former studies the integration of the European market and provides evidence of home bias in vehicle demand across European countries. The latter uses similar data from six European countries, Brazil, Canada, and the US and concludes that consumer preference for domestic brand, rather than supply-side considerations, is the main contributing factor to home bias. Our study adds to this literature by showing that local governments' policies and practices could be another important factor in shaping the geographic variation in market shares.

The automobile market in China provides a unique setting to study the formation of brand preferences that is different from the studies cited above, because most vehicle buyers are first-time consumers of cars. The literature on the persistence of demand preference suggest that protective policies could have long lasting effects. Even if these policies are eliminated as China embraces more reforms and emulates practices in developed countries, they could still affect future market share dynamics through persistent brand preference. Our welfare estimates could be vastly underestimating the long-term efficiency loss induced by these policies.

Second, our paper contributes to the literature on understanding the sources of resource misallocation and its implications on productivity and economic growth. Fajgelbaum et al. (2016) examine the impact of state taxes on spatial resource misallocation and show that equalizing state taxes can increase worker welfare and aggregate output. Hsieh and Klenow (2009) document a much larger dispersion in the marginal product of capital and labor across firms in China and India than those observed in the U.S.. Brandt et al. (2009) estimate that the distortions in factor allocation in China reduce aggregate TFP by about 30% on average from 1985 to 2007, with the within- and between-province distortions accounting for similar portion of the reduction. These studies have focused on the input market and argued that financial and labor market imperfections could limit the free flow of capital and labor. Different from the previous literature, our analysis focuses on the market frictions induced by government policies in a product market. We show that such frictions increase the market power of some firms at the expense of others, resulting in inefficient production allocation and ultimately misallocation of inputs across heterogeneous firms.

Third, our paper adds to the emerging literature on understanding intra-national trade barriers and spatial patterns of production specialization. Within the trade literature, recent studies have quantified the importance of geography in trade costs using data from both developing and developed countries (Anderson et al., 2014; Atkin and Donaldson, 2016; Cosar and Fajgelbaum, 2016). Our paper points to local discriminatory policy as another source of trade costs. These protective policies against non-local firms are hard to measure since they vary across space and time and are often implicit. Using province level industry aggregate output, previous studies have provided evidence of local protectionism by detecting regional specialization that deviates from comparative advantage of input factors (Young, 2000; Bai et al., 2004; Holz, 2009). Our study documents local protectionism in a consumer good industry by showing that local products enjoy home bias that cannot be explained by transportation cost, sales network, and preference heterogeneity. More importantly, our paper is the first to quantify the impacts of local protectionism on market outcomes and social welfare, an important step toward understanding the market structure in an emerging economy.

The rest of the paper is organized as follows. Section 2 presents an overview of the automobile industry in China, discusses the institutional background and anecdotal evidence of local protectionism, and describes our data. Section 3 provides evidence of local protectionism using a spatial regression discontinuity analysis and establishes local protectionism as the leading explanation for SOE's and JV's home bias using falsification tests and a consumer survey. Section 4 sets up a market equilibrium model of vehicle demand and supply and discusses the identification strategy. Section 5 presents results from the structural model. Section 6 conducts simulations to quantify the welfare impact of local protectionism. Section 7 concludes.

2 Background and Data

In this section, we first present anecdotal evidence of local protectionism and discuss the relevant institutional background. We then provide an overview of China's automobile industry and describe the data.

2.1 Local Protectionism

We define local protectionism as policies and practices that protect local firms against competition from non-local firms. In the automobile market, a common practice is to give consumers direct subsidies or tax incentives for purchasing local products, where the definition of a "local" product is tied with different requirements across jurisdictions.[2]

[2] Yu et al. (2014), an article in Wall Street Journal on 5/23/2014, reports that government subsidy to 22 publicly traded automakers in China amounted to 2.1 billion Yuan in 2011 and this number increased to 4.6 billion in 2013. The article acknowledges that "(t)he subsidies come in many forms, including local government mandates and subsidies

Table 1: Examples of Local Protectionism

Case	From	To	Location	Size	Eligibility
1	3/1/09	12/31/09	Hebei	10% or 5000	Local minivans
2	7/1/09	12/31/09	Heilongjiang	15% or 7500	Local brands
3	8/18/09	unkown	Henan	3% or 1500	Local brands in Henan
4	1/1/12	12/31/12	Chongqing	total 300mil.	Changan Automotive
5	4/4/12	12/31/12	Anhui	3000	Local brands for Taxi
6	7/1/12	6/30/13	Changchun, Jilin	3500-7000	FAW indigenous brands
7	1/1/14	12/31/14	Chongqing	total 70mil.	Changan Automotive
8	4/16/14	unkown	Xiangtan, Hubei	2000	Geely Automotive
9	5/1/15	4/30/16	Fuzhou, Jiangxi	5%-10%	Jiangling Automotive
10	11/15/15	12/15/15	Guangxi	1500-2000	Local brands

Source: Official government documents from online searches. Unit in Yuan.

From online searches with the keywords "subsidy + promote automobile industry", we compile a list of policies in the past few years that subsidize buyers of local brands using direct monetary transfer, tax and fee waivers, or low-interest loans. Table 1 presents ten cases of subsidy with explicitly stated compensation amount for products that are produced either by designated local automakers or in the jurisdiction. The 6th case is worth noting in that the subsidy only applies to indigenous brands produced by the state-owned subsidiaries of the First Auto Works group (henceafter FAW), but not to the brands by the JV subsidiaries of FAW.[3]

Besides direct subsidies, local protectionism comes in many other forms: explicit requirements for government agencies and taxi companies to purchase local brands; procurement priority or tailpipe emission standards that favor local brands; and explicit and implicit barriers for non-local brands to establish dealer network. The common theme of the stated rationale behind these policies in official government documents is to increase employment, strengthen the local automobile industry and in turn the local economy.

It is important to note that the local protectionism or various trade barriers more generally that we analyze here is not about physical barriers related to a poor transportation infrastructure. Highways, the railway systems, as well as supply chain management have improved dramatically in China during the last decade (Faber, 2014).

Local protectionism in China arises from a combination of factors. First, market reforms started in 1978 made economic development the primary responsibility for local governments. GDP growth became an essential measure of performance in the top-down political personnel system where local officials (provincial governors, city and county mayors) are evaluated by government

for purchases of locally made cars, making a total figure for local and national financial help difficult to calculate."

[3]FAW is one of the largest automakers in China. It has three state-owned subsidiaries producing indigenous brands such as Besturn and three JV subsidiaries producing Volkswagen, Toyota, and Mazda models.

officials at the higher level.[4] In addition, the fiscal decentralization whereby local expenditures are mostly financed by local revenue provides officials incentives to seek a strong local economy (Jin et al., 2005). Both the promotion system and fiscal decentralization lead to inter-jurisdictional competition and discriminatory policies that protect local firms against competition from non-local firms.

A famous example is the 'war of license fees' between Shanghai and Hubei province in the late 1990s. Starting from the early 1990s, Shanghai municipal government implemented Reserve Price auctions for vehicle license plates. Vehicle buyers were required to pay for the license plate before registering their newly purchased vehicles. In 1999, in the name of promoting the growth of local automobile industry, Shanghai government set the reservation price to 20,000 yuan for local brands (e.g. Santana produced by Shanghai Automotive) and 98,000 yuan for non-local brands. In retaliation, Hubei province, the headquarter province of China's Second Automotive Group, charged an extra fee of 70,000 yuan to Santana consumers "to establish a fund to help workers of companies going through hardship" .

Second, local government officials often derive private benefits from local SOEs and JVs. Local governments appoint the top executives of SOEs and JVs in their jurisdiction and there exists a revolving door between top executives in these companies and government officials. A a result, local government officials can directly benefit from local SOEs in many ways, ranging from finding jobs for their relatives in these companies to eliciting monetary support for public projects and even private usage.[5]

Third, the central government has not been very effective in regulating inter-regional trades. While the literature of fiscal federalism points out the potential benefit of allowing local governments to make better-informed decisions on public goods provision, it also acknowledges the pitfalls of regional protectionism and allocative distortions (Oats, 1972). The central government plays an important role in addressing these pitfalls through promoting a national market and eliminating trade barriers. The Commerce Clause in the U.S. Constitution explicitly prohibits state regulations that interfere with or discriminate against interstate commerce. This to a large extent frees the U.S. market of local protective policies observed in China, although some inter-state trade barriers also persist in the U.S. (Fajgelbaum et al., 2016). Although China's Anti Unfair Competition Law, passed in 1993, explicitly prohibits municipal or provincial governments from giving preferential treatment to local firms, enforcement of the law has not been very effective.

As Table 1 shows, local protectionism often manifests as differential treatment for firms with different ownership types. SOEs are treated most favorably because of their importance in the lo-

[4]The effectiveness of the one-child policy used to be an important criterion. In recent years, environmental measures are added to the evaluation system.

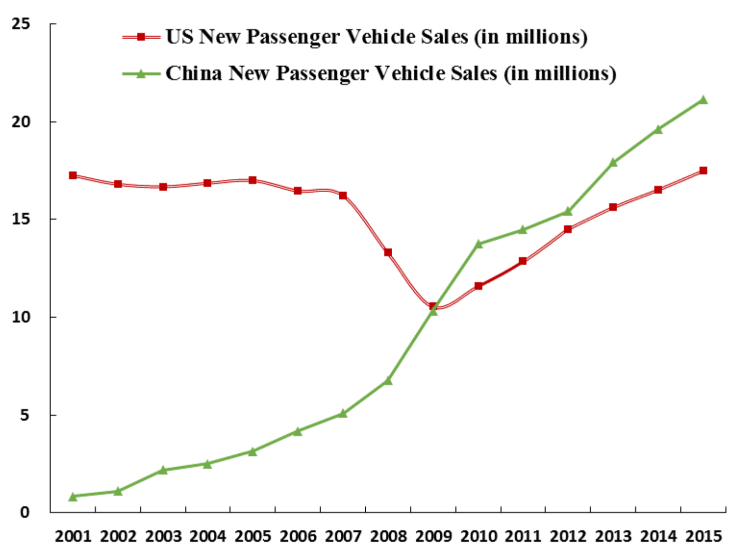
[5]This has been highlighted by many recent high-profile corruption cases in China where government officials were convicted of taking eye-popping bribes from executives of large companies in their jurisdiction.

cal economy and close ties between SOE top executives and local government officials. JVs lie between SOEs and private firms in the spectrum of differential treatment. By law, JVs are owned in majority by Chinese automakers and in practice, the Chinese partners are all SOEs. In the empirical analysis, we measure the degree of local protection for SOEs, JVs, and private automakers separately. Consistent with Bai et al. (2004) which finds stronger local protectionism in industries where SOEs account for a larger output share, our empirical analysis shows that local protectionism benefits SOEs the most and JVs the second.

2.2 The Chinese Automobile Industry

Like many other industries, China's automobile industry rose from virtually non-existent thirty years ago to the top of the world at an astonishing speed. Figure 1 depicts the annual sales of new passenger vehicles in U.S. and China. The total number of new passenger vehicle sales in China increased from 0.85 million in 2001 to 21.1 million in 2015, surpassing the U.S. to become the largest market in the world in 2009. The growth in China's automobile market during this period accounted for about 75 percent of the growth in the world automobile market.

Figure 1: New Passenger Vehicle Sales in China and U.S.



All major international automakers currently have production capacity in China. Following the strategy of "exchange-market-for-technology", or "Quid Pro Quo" (Holmes et al., 2015), Chinese government requires foreign automakers to form joint ventures with domestic automakers in order to set up a production facility. The non-Chinese parties combined in a joint venture cannot claim more than 50 percent of the ownership. A purpose of such a requirement is to help domestic automakers to learn from foreign automakers and eventually compete in the international market. Volkswagen was the first to enter the Chinese market by forming a JV with Shanghai Automotive in 1983. To date, Volkswagen and GM have the largest presence in China among foreign automakers.

For its potentially large contribution to local employment and GDP and its spillover benefits to upstream industries, the automobile industry is a frequent target for government protection. Provinces compete to provide financial incentives to attract automakers. As a result, automobile production currently exists in 26 out of 31 provinces. During China's 11th Five Year Plan from 2005 to 2010, all of these provinces designated the automobile industry as a strategic industry that enjoy tax benefits and various other government support.

Perhaps not surprisingly, China's automobile market is much less concentrated and the average output of each automaker is smaller compared to the U.S.. In 2015, there are over 60 automakers producing in China and the top six dominant firms account for 46% of market shares. After years of rapid expansion, the Chinese auto industry is plagued with overcapacity, with an average capacity utilization rate of merely 65%. In contrast, in the U.S., there are fifteen automakers and the top six firms control 77% of the market. The automobile assembly plants are located in 14 out of 50 states, with an average capacity utilization rate around 85%.[6]

2.3 Data

Our analysis is based on four main data sets: (1) the universe of individual vehicle registration records from 2009 to 2011 that is compiled by the State Administration of Industry and Commerce, (2) trim level vehicle attributes from R. L. Polk & Company (henceforth Polk), (3) city level household demographics from the 2005 one-percent population survey, and (4) an annual survey of new vehicle buyers by Ford Motor Company.

For the vehicle registration data, we observe the month and county of registration, the brand and model name of the vehicle registered, as well as major attributes such as transmission type, fuel type, and engine size. We also observe whether the license is for an individual or institutional purchase. Institutional purchases account for about 10% of all registration records. As one might expect, institutional purchases exhibit a much greater extent of home bias (appendix C). We focus on individual purchases in this study since institutional purchases are often driven by non-market considerations that require a different model. We aggregate data to the model-county level for the spatial discontinuity analysis in Section 3, and to the model-province level for the structural estimation in Section 4. To translate the number of registration records, or sales, into market shares,

[6]According to a 2013 OECD report titled "Medium-Run Capacity Adjustment in the Automobile Industry", the capacity utilization in China's automobile industry was 64 percent in 2012, compared to 83 percent in both U.S. and Japan and 84 percent in Germany.

we define market size as the number of Chinese households in each province.[7] JVs contribute to 68.7% of total sales during our sample period. Private automakers, SOEs, and imports account for 11.4%, 16.7% and 3.1% of total sales, respectively.

The trim-level vehicle data report the manufacturer suggested retail price (MSRP), vehicle type (sedan, SUV, or MPV), vehicle size (m^2), engine size (liter), horsepower (kilowatts), weight (ton), transmission type, and fuel type. MSRPs are set by manufacturers and are the same nationwide for each model-year. Discounts offered by individual dealers may lead to transaction prices that are different from the MSRPs. According to a 2016 store-level promotion data that is discussed in detail in Appendix B, there are small regional variations in retail prices.[8] However, we believe that MSRP is a decent approximation of transaction price (which we do not observe) in our study for two reasons. First, heavy discounts are rare: around 40% of trim-by-store observations have no discount, 25% have a 10% discount, and only 3% have a 20% discount. More importantly, dealer stores do not give more discount to local products, which suggests that using MSRP in place of the transaction price will not bias the estimation of local protection.

MSRP in China includes value-added tax, consumption tax, as well as import tariffs when applicable.[9] It does not include sales tax, which is normally set at 10% but is reduced to 5% and 7.5% for vehicles with engine displacement no more than 1.6 liter in 2009 and 2010, respectively. We add sales tax to MSRP, and deflate it to the 2008 level to obtain the real transaction price paid by consumers. We choose engine size over horsepower-to-weight ratio as a measure of acceleration because engine size is known to be a more salient feature for auto buyers in China.

We define a model by its model name, vehicle type, transmission type, and fuel type. Trim level attributes are aggregated to the model level via a simple average, and then matched to our registration data. Price and attributes for each model are constant across all markets in a given year, but exhibit between-year variations due to price updates, introduction of new trims, and withdrawal of old trims. To construct a measure of fuel economy, we first collect information on the fuel consumption per 100km for each model from the Ministry of Information and Industrial Technology (MIIT). Then we multiply it with the province-year gasoline price to obtain the average fuel cost in yuan per 100km.

[7] While some consumers might purchase a new vehicle in one province and register it in another province, this is uncommon since dealers typically bundle services with the sale price of a new vehicle.

[8] We collect the promotion data from Autohome.com, a major privately-run gateway website that regularly updates information on car features and industry headlines. Minimum Retail Price Maintenance (RPM) whereby automakers prohibit dealers from selling below a preset price has been common in China. For example, the China Automobile Dealers Association complained in 2011 that large automakers had been imposing RPM and exclusive territory to reduce price-competition among dealers. This did not draw attention from China's antitrust authority until very recently. As in the U.S., RPM is not treated as per se illegal by China's antitrust authority and each case has to be judged based on individual merits.

[9] Consumption tax is levied to promote sales of small and fuel-efficient vehicles. It varies from 1% to 40%, depending on vehicle size.

Besides prices and attributes, another important factor for auto demand is the dealer network. Due to the lack of historical data, we use a cross section of dealer counts by brand and province in March 2016 to approximate the dealership network during our sample period. According to reports by China Auto Dealers Association (CADA), the number of dealer stores in China increased from 13,000 in 2009 to 24,000 at the end of 2014. Appendix A shows that automakers have a more extensive dealer network in their home market than in other provinces, but the differences are not as large as those observed in sales, suggesting that dealer network only partially explains the home bias in sales.

Information on headquarter and plant locations is obtained from each firm's website. Our final consists of 38 domestic firms and 14 foreign firms. The domestic firms include 6 private firms, 20 JVs, and 12 SOEs. No firm moved its headquarter within our sample period, and only two opened new plants. For each model produced by a domestic firm, we find the commuting distance between its plant location and each of its destination markets.

Our raw dataset contains a total of 683 models. Many of them are only sold in a few provinces with very low sales. We keep the most popular models that account for 95% of national sales in each year. Doing so has several benefits. First, sales of small brands are likely measured with errors. Second, and more importantly, since we focus on analyzing differences between vehicle models' local shares and national shares, limiting to major national brands gives us a conservative measure of local protectionism. For example, some brands might not be marketed nationally. Including them in our analysis would exaggerate the extent of local protection. Third, obtaining counterfactual equilibrium prices is computationally challenging when we have a demand system with a large number of products. We also drop models priced above 800,000 RMB (about $123,000), as demand for these luxury brands is likely driven by conspicuous consumption or other factors not captured in our stylized model. That leaves us with a total of 179, 218, and 234 models in each year. Choice sets across provinces in any given year do not vary much. For example, in 2011, 25 out of 31 provinces have all 234 models. The choice set does exhibit variation over time, due to entry and exit of vehicle models. The total number of observations in our final sample is 19,505.

Table 2: Summary Statistics of Key Variables

Variable	Mean	Std. Dev.	Min	Max
Sales	1259	2263	1	60612
Real price (1000 yuan)	184.7	144.5	27.5	798.7
Fuel cost (yuan/100 km)	50.1	10.0	24.9	101.2
Engine size (liter)	1.8	0.5	0.8	4.0
Vehicle size (m^2)	7.7	0.9	4.2	10.3
Auto transmission	0.48	0.50	0	1
SUV	0.17	0.37	1	0
MPV	0.06	0.24	0	1
Number of dealers	20.8	23.3	0	137
Distance to headquarter (1000km)	2.1	1.4	0	5.2

Note: The number of observations is 19,505. Sales are monthly sales by model and province. The number of dealers is by province and brand.

Table 2 reports the summary statistics. The average price of a vehicle is 184,700 Yuan (about $28,000). The average price is similar to that observed in the U.S. market but the price range is larger in China. The indigenous brands from domestic automakers tend to occupy the low-end segment while the JVs and imports compete in the high-end segment. Among the brands from JVs and imports that are also available in the U.S. market, our price comparison shows that the prices for entry models (such as Ford Focus and Toyota Corolla) are similar in the two markets but those for luxury brands can be twice as expensive in China as in the US. The price difference for these vehicles can be attributed to the high consumption tax (as high as 40% of the wholesale price), the nature of demand (e.g., conspicuous consumption), and market competition (Li et al., 2015).

Table 3 below shows that different types of firms have very different product mix. JV brands on average have a higher price, vehicle size, and engine size compared to private or SOE brands. The price difference between JV products and their domestic counterparts is much larger than the difference in the observed attributes. Higher prices are largely driven by better brand recognition and higher unobserved qualities, which we capture using brand fixed effects in our estimation. In addition, JVs have a more extensive dealer network, and a larger fraction of their products have automatic transmission. Imported products are typically luxury brands, and majority of them are SUVs.

Table 3: Mean values of Key Variables by Firm Type

Variable	Private	JV	SOE	Imports
Sales	1271	1443	1118	382
Real price (1000 yuan)	80.0	188.3	96.0	428.1
Fuel cost (yuan/100 km)	45.7	49.7	47.7	61.7
Engine size (liter)	1.5	1.8	1.6	2.5
Vehicle size (m^2)	7.2	7.9	7.4	8.3
Auto transmission	0.06	0.55	0.17	1
SUV	0.20	0.11	0.10	0.56
MPV	0	0.04	0.15	0.11
Number of dealers	13.1	26.3	11.6	12.0
Number of observations	2230	11907	3363	2005

Note: Sales are monthly sales by province. The number of dealers is by province by brand.

Rising household income is perhaps the most important factor that drives China's exponential growth in vehicle sales since the mid 2000s. To account for the impact of income on vehicle demand, we obtain empirical distributions of household income at the province level from China's 1% population survey in 2005, separately for urban and rural households. Such comprehensive data at the individual level or county level for recent years are difficult to find. Consequently, for each year in our sample period, we scale each provincial income distribution from the 2005 survey such that its mean matches the provincial average from the annual China Statistical Yearbooks.[10] By using the 2005 census data, our implicit assumption is that the shape of income distributions in China did not change significantly between 2005 and 2011.

Besides the income distribution for the general population, we also obtain the income distributions for new vehicle buyers from an annual survey conducted by Ford Motor.[11] The survey breaks annual household income into four brackets: less than 48k Yuan, 48k-96k Yuan, 96k-144k Yuan, and greater than or equal to 144k Yuan, and reports the fraction of vehicle buyers from each income bracket in each year. It further divides vehicles into 24 types and reports the fraction of car buyers in each income bracket for each vehicle type. We aggregate the 24 types into five segments: mini/small sedan, compact sedan, medium/large sedan, sport utility vehicle (SUV), and multi-purpose vehicle (MPV).

The first panel of Table 4 compares the income distribution among all vehicle buyers to that of the general population. The second panel of Table 4 reports the income distribution of consumers for each of the five vehicle segments in 2011. Consumers with a higher household income are disproportionately more likely to buy new vehicles, especially high-end sedans, SUVs, and MPVs. In 2011, only 4% of households in China have annual income above 144k, which is the median

[10] In 2010, the average household income in China is about one seventh of that in the U.S..

[11] The survey covers 20,293, 22,915, and 33,961 vehicle buyers in 2009, 2010, and 2011, respectively.

Table 4: Micro-moments: Fraction of Vehicle Buyers by Annual Income

(a) Fraction of Households by Annual Income (yuan)

Year	< 48k	48k – 96k	96k – 144k	≥ 144k
Among Vehicle Buyers				
2009	0.16	0.34	0.32	0.19
2010	0.11	0.27	0.32	0.30
2011	0.09	0.26	0.34	0.31
Among All Households				
2009	0.69	0.23	0.05	0.03
2010	0.63	0.27	0.06	0.04
2011	0.55	0.33	0.08	0.04

(b) Fraction of Buyers by Income Brackets for Different Vehicle Segments, 2011

Segment	< 48k	48k – 96k	96k – 144k	≥ 144k
Small/mini sedan	0.15	0.40	0.30	0.15
Compact sedan	0.11	0.30	0.37	0.22
Medium/large sedan	0.05	0.16	0.32	0.47
SUV	0.05	0.15	0.33	0.47
MPV	0.07	0.24	0.33	0.36

price of a car in our sample. Yet they account for 47% of the sales of medium/large sedans and SUVs, and 36% of MPVs. The information on consumer income distribution is used to form micro-moments in our estimation as in Petrin (2002) and helps us to separately identify price elasticity and income elasticity.

3 Descriptive Evidence and Spatial Discontinuity

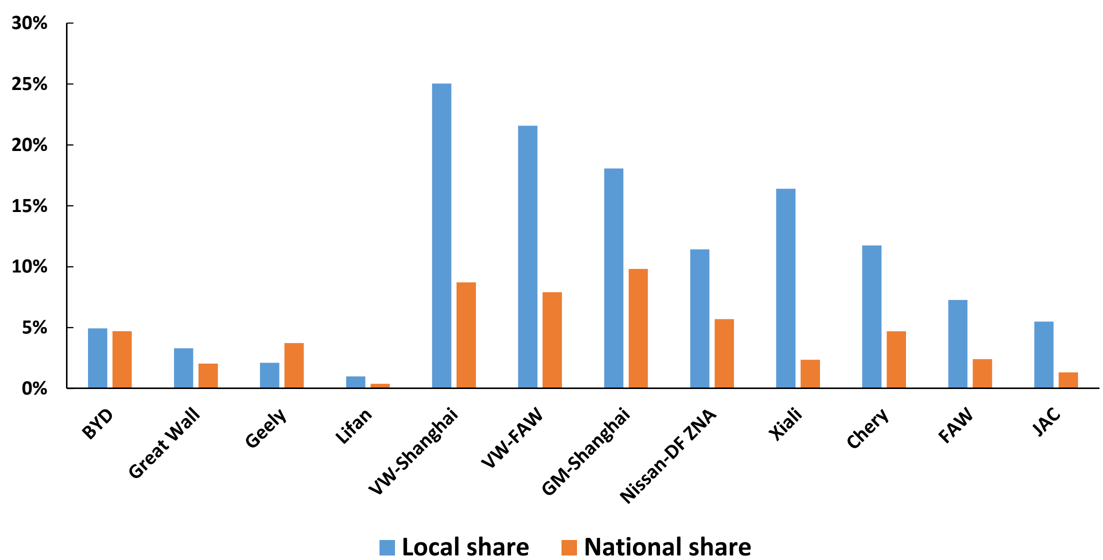
We first provide descriptive evidence on the strong home bias enjoyed by JVs and especially SOEs. Then we use a spatial regression discontinuity analysis and a series of falsification tests to show that local protectionism is the leading cause of home bias.

Home bias is well documented in the trade, finance, and marketing literature (French and Poterba, 1991; McCallum, 1995; Klein and Ettensoe, 1999). It is typically though not exclusively observed in the international context with respect to products from different countries (e.g., a country-of-origin effect). Our analysis focuses on interregional trade and the home bias we study is a province-of-origin effect (based on vehicle assembly) within a country.

3.1 Descriptive Evidence

To graphically illustrate differences in sales between the home province and the national market, Figure 2 contrasts the market share at the national level with that in the headquarter province for selected automakers. The first four are private automakers, the next five JVs, and the last five SOEs[12]. For non-private firms, especially SOEs, market shares in their local market are significantly higher than those at the national level. One notable example is Xiali: it accounts for only 2.36% of national new vehicle sales but enjoys a market share of 16.4% in its home province Tianjin. There is no noticeable home bias for most private automakers. Appendix A provides the comparison for a comprehensive list of automakers: across the board, SOEs exhibit the strongest home bias and private automakers the least.

Figure 2: National and Home-Province Market Shares



Besides local protectionism as we discussed in Section 2.1, there are a number of reasons that could to lead to this disparity. First, transportation costs are lower in the local market. However, transportation costs do not have an impact on demand unless they are reflected in vehicle prices. MSRP is the same across all markets for each model in our sample, and our promotions data do not show any appreciable difference between dealer discounts in local and non-local markets. This suggests that firms are absorbing the higher transpiration costs (they typically account for one to two percent of vehicle prices) in markets further away from their production facilities instead of passing them through to consumers. Nonetheless, vehicle demand could depend on distance since

[12]For each firm type, we select firms that have the largest national market shares. These twelve firms together account for over 60% of total vehicle sales in China between 2009 and 2011.

nearby consumers have better information about a product and greater exposure to local advertising. In this section, we focus on counties that border with each other and hence have similar distances to the production facilities. In the structural analysis in the next section, we control the distance between the production location and the destination market.

Second, appendix A shows that brands produced in the home province have more extensive dealer networks. However, the differences in dealer network between the national market and the home market are typically smaller than those in sales. In our analysis, we control for the number of dealers by brand either by focusing on adjacent counties or including the number of dealers by brand in the regression explicitly. It is worth noting that the observed differences in dealer network could be partly driven by local policies and practices that treat dealers of local brands more favorably in the process of issuing dealer license permits.

Third, there could be a better compatibility of consumer preference and local products. For example, many JVs have headquarters in high-income markets such as Beijing, Shanghai, and Guangdong, and sell expensive foreign brands that are popular among wealthy households. Similarly, SOEs that produce low-priced indigenous brands tend to locate in less wealthy provinces such as Anhui, Jilin, and Liaoning. The better match between household income in the home market and the market segment could lead to larger market shares locally than nationally for these products, as documented in Cosar et al. (2016). We include income, arguably the most important household demographics, in our analysis in addition to a variety of fixed effects such as provincial fixed effects, and their interaction with vehicle type. In addition, we conduct falsification tests below and the results suggest that this is unlikely to be an important factor.

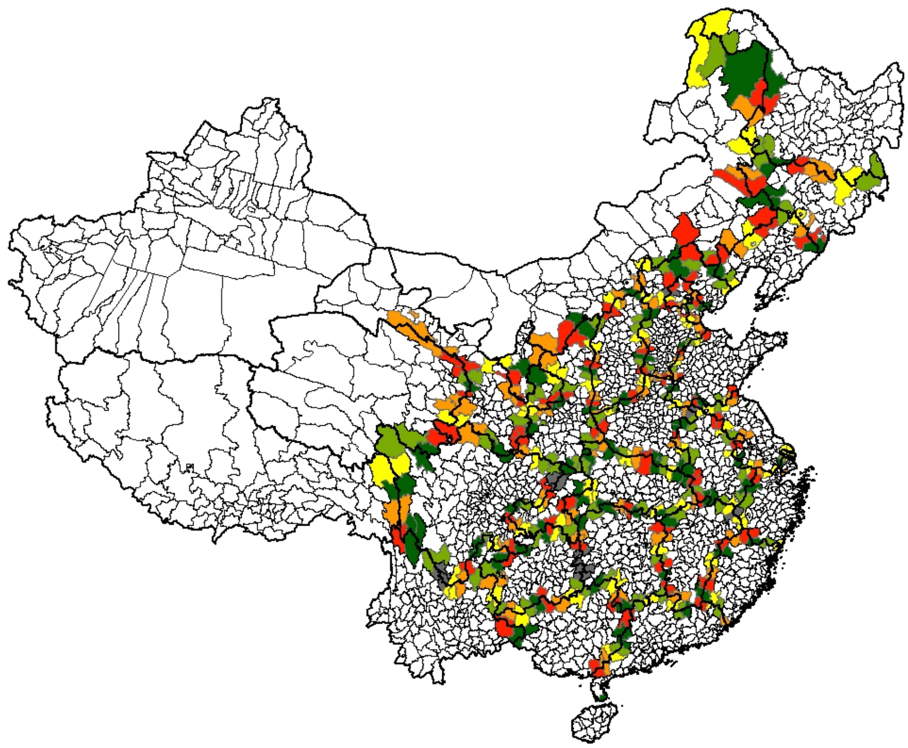
Fourth, there could exist an innate preference for locally produced vehicles due to consumer ethnocentrism whereby consumers in one group (typically a country) may view purchasing products from another group being inappropriate or maybe even immoral because doing so could hurt local economy or for other considerations(Shimp and Sharma, 1987). Consumer ethnocentrism or animosity could give rise to the country-of-origin effect and is well studied in the marketing literature (Klein and Ettensoe, 1999; Canli and Maheswaran, 2000). It is important to note that consumer sentiments such as ethnocentrism is often studied in the context of products from different sovereign countries, our research focuses on interregional trade within China.

Last, discounts to company employees could also increase local sales.

3.2 Spatial Regression Discontinuity

Using our county-level vehicle sales data, we employ a proof-by-elimination strategy in which we carefully rule out each of the the five factors discussed earlier as the main driver of home bias in vehicle demand, and thereby identify the effects of local protectionism. Our main empirical strategy is a spatial discontinuity design in which we limit our analysis to clusters of adjacent counties across provincial borders. We focus on provinces that house headquarters of automakers and group counties into different clusters, each of which contains two or three adjacent counties on different sides of a provincial border. We leave out counties along the borders of Tibet, Xinjiang, and Qinghai, since these counties are too large for our identification assumptions. Our final sample consists of 630 counties in 285 clusters as shown in different color in Figure 3.

Figure 3: Clusters of Counties along Provincial Borders



The spatial discontinuity design takes advantage of the fact that provincial borders lead to discontinuity in the types of protective policies and practices discussed in Section 2.1, while assuming similar consumer preference across the borders. We focus on the differences within each cluster and control for cluster-specific preferences for different brands, e.g., one cluster of counties may prefer SUVs over sedans due to road conditions. The underlying assumption is that because of the geographic proximity, consumers within the cluster have similar taste for vehicles (i.e., no discontinuity at the border) and similar access to information and dealer stores . The key empirical pattern of interest is whether the differences in market shares persist within each cluster, that is, whether brands sell much better in a county within the home province than the nearby county across the border. We focus on the standard RD regressions in this section and provide further supporting evidence through falsification tests and intra-province analysis in next section.

We implement the spatial discontinuity design in the logit framework using county-level sales data following Berry (1994):

$$\begin{aligned} ln(\frac{s_{jm}}{s_{0m}}) &= \beta_1 \text{HQ}_{jm}\text{PRI}_j + \beta_2 \text{HQ}_{jm}\text{JV}_j + \beta_3 \text{HQ}_{jm}\text{SOE}_j \\ &\quad + \gamma_1 \text{PL}_{jm}\text{PRI}_j + \gamma_2 \text{PL}_{jm}\text{JV}_j + \gamma_3 \text{PL}_{jm}\text{SOE}_j \\ &\quad + \phi_{jc(m)} + \delta_m + \eta_t + \xi_{jmt}, \end{aligned} \tag{1}$$

where s_{jm} stands for the market share of product j in county m, and s_{0m} stands for the share of the outside option. Cluster-model fixed effects, $\phi_{jc(m)}$, control for differences in consumer preferences across clusters. The implicit assumption is that consumers in counties within the same cluster have the same preference for each model. After further controlling for county fixed effects and year fixed effects, we identify our parameters of interest, β_1 to β_3, from the difference in market shares by firm type between home-market and non-home-market counties within the same cluster. We also look at whether plant presence in some non-home-province leads to an increase in demand. [13]

The spatial discontinuity design tests whether observed home bias survives after controlling for a number of confounding factors discussed above. More specifically, it controls for distance, dealership network, and to a limited extent consumer demographics. Within the same cluster, each brand has similar market access to all counties since it is easy to commute to a dealer located in an adjacent county.[14]

Table 5 summarizes the results. Columns (1) and (2) control for model fixed effects. Column (1) includes all 2336 counties in our full sample, while column (2) only includes the 630 counties along provincial borders. Results in columns (1) and (2) are similar, indicating that the magnitude of home bias does not differ significantly in the set of bordering countries from that in the full sample. Home advantage for private products is negative but small in column (1) and statistically insignificant across all other specifications. The estimates of β_1 and β_2 reflects the captures of home bias: sales for JVs and SOEs in their home markets are higher by 82% and 180%, respectively.

Columns (3) and (4) implement the spatial discontinuity design by including cluster-model fixed effects following the identification strategy described earlier. Column (4) restricts the sample to 373 counties that have similar GDP per capita within a cluster. The home bias for JVs and SOEs only reduces moderately from column (2): down from 82% to 52% for JVs and from 180% to 159% for SOEs in column (3). Results in columns (3) and (4) are very similar. The large β estimates that survive the control of cluster-model fixed effects suggest that distance, access to dealers and consumer demographics are not the drivers of home bias observed in our data. The results also show that SOEs, but not JVs or private automakers, also enjoy higher demand in non-home markets

[13] PL_{jm} takes value 1 in all counties in a province that is not the headquarter province for model j, but has a plant by the firm that produces model j.

[14] When one buys a car in another county, the registration will occur at the county of residence and is recorded so in our data.

where they have production facilities.

Table 5: Results from the spatial discontinuity model

	All	All	Clusters	Clusters
	(1)	(2)	(3)	(4)
HQ*Private, β_1	-0.16***	-0.00	0.12	0.12
	(0.04)	(0.07)	(0.08)	(0.11)
HQ*JV, β_2	0.68***	0.60**	0.42***	0.41***
	(0.03)	(0.06)	(0.03)	(0.04)
HQ*SOE, β_3	1.09***	1.00***	0.95***	0.94***
	(0.03)	(0.05)	(0.04)	(0.06)
PL*Private, γ_1	0.26***	0.21***	0.02	-0.08
	(0.04)	(0.07)	(0.07)	(0.11)
PL*JV, γ_2	0.15***	0.18**	0.03	-0.07
	(0.02)	(0.04)	(0.045)	(0.06)
PL*SOE, γ_3	0.63***	0.61***	0.42***	0.51***
	(0.04)	(0.08)	(0.079)	(0.08)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Model FE	Yes	Yes	No	No
Cluster-model FE	No	No	Yes	Yes
No. of counties	2336	630	630	373
No. of obs.	885376	180398	180398	96058

Notes: In column (4), we restrict the sample to clusters where the ratio between the highest and lowest GDP per capita across counties within the cluster is no larger than 1.6. p<0.1, ** p<0.05, *** p<0.01.

Cosar et al. (2016) document that a country-of-origin effect of 240 percent in vehicle demand based on data from nine countries. They show that consumer preference for products that are originated or assembled from the same country accounts for nearly 70 percent of the home bias, with supply side factors (tariff and trade barriers) and dealer network explaining the rest. In China, imports account for less than 7% of new vehicle sales today, and hence our focus is on vehicles produced within China. The home bias in this study captures the province-of-origin (in terms of assembly) rather than the country-of-origin effect.

We argue that consumer ethnocentrism (an innate preference for local products), the fourth factor discussed above, is also unlikely to be a significant driver of home bias. Our RD analysis shows that private automakers do not have any appreciable advantage in their home markets while JVs and SOEs do. For consumer ethnocentrism to be an important factor, one has to argue that the innate preference for local brands only applies to SOEs and JVs but not private automakers. There is no reason to believe that this should be the case: few consumers know the differences in ownership structure, especially between SOEs and private automakers. This is confirmed from a survey of Chinese consumers who recently bought a car. We conducted a pilot study at dealer stores in an affluent province in eastern China that accounts for about 10% of national sales. Our results indicate that few car buyers in China can tell whether an auto maker is private or an SOE. A surprisingly low fraction of consumers can recognize a JV, even though all of these firms' names prominently feature the name of their foreign partner (e.g. BMW Brilliance).

To examine the impact by employee discount, we look at the degree of home bias at the production counties, where the company employees are likely to reside. We estimate the following model:

$$\begin{aligned} ln(\frac{s_{jm}}{s_{0m}}) &= \beta_1 \text{HQ}_{jm}\text{PRI}_j + \beta_2 \text{HQ}_{jm}\text{JV}_j + \beta_3 \text{HQ}_{jm}\text{SOE}_j \\ &\quad +\alpha_1 \text{OwnPL}_{jm}\text{PRI}_j + \alpha_2 \text{OwnPL}_{jm}\text{JV}_j + \alpha_3 \text{OwnPL}_{jm}\text{SOE}_j \\ &\quad +\theta_1 \text{OtherPL}_{jm}\text{PRI}_j + \theta_2 \text{OtherPL}_{jm}\text{JV}_j + \theta_3 \text{OtherPL}_{jm}\text{SOE}_j \\ &\quad +\rho_j + \delta_m + \eta_t + \xi_{jmt}, \end{aligned} \tag{2}$$

OwnPL_{jm} takes value 1 if county m is the production county for model j. OtherPL_{jm} takes value 1 if county m is not the production county for model j, but has a plant owned by the firm (it produces some other model by the firm). 17 out of the 38 firms in our sample have production plants in at least two different counties, each of which produces a different set of models. In this specification, we identify the α and θ parameters by comparing sales in the production counties with other counties in the same province. Table 6 below shows the estimation results.

Table 6: Home Bias at the production counties

	(1)		(2)	
	Est.	SE	Est.	SE
HQ*Private, β_1	-0.17***	0.04	-0.17	0.04
HQ*JV, β_2	0.66***	0.03	0.66***	0.03
HQ*SOE, β_3	1.07***	0.03	1.06***	0.03
OwnPL*Private, α_1	0.72***	0.17	0.68***	0.18
OwnPL*JV α_2	0.90***	0.22	0.91***	0.22
OwnPL*SOE α_3	0.92***	0.32	0.90***	0.32
OtherPL*Private θ_1			-0.27***	0.03
OtherPL*JV θ_2			0.11***	0.02
OtherPL*SOE θ_3			-0.25	0.23
No. of obs.	885376		885376	
No. of counties	2336		2336	

Notes: We control for model, county, and year fixed effects.
* p<0.1, ** p<0.05, *** p<0.01.

We see significant home bias in the production county, but not in other plant locations by the same firm. Such results suggest that employee discount is unlikely to be a key driver of home bias. Employee discounts typically cover all products under a firm, instead of just the models produced in the plants where the employees work. Therefore, if employee discounts have a large impact on demand, we should expect positive and significant estimates for the θs.

An interesting result from Table 6 is that models by all three types of firms, including the private automakers, have significant home bias in their production counties (in addition to the home bias in the headquarter province). The result suggests that there could be some consumer ethnocentrism near the production sites[15], but it dissipates rapidly once we move out of the production county.

Table 7 below shows results from a specification in which we interact the HQ dummy with distance from the production county. The unit of distance is 1000 km. The median distance in our sample is 0.16 (160km), while the maximum distance is 0.6 (600km). The reference group is counties outside the headquarter province.

Table 7: Home bias within the headquarter province

	(1)		(2)	
	Est.	SE	Est.	SE
HQ*Private, β_1	-0.17***	0.04	-0.14**	0.06
HQ*JV, β_2	0.66***	0.03	0.81***	0.05
HQ*SOE, , β_3	1.07***	0.03	1.28***	0.06
OwnPL*Private, α_1	0.72***	0.17	0.70***	0.18
OwnPL*JV, α_2	0.90***	0.22	0.75***	0.22
OwnPL*SOE, α_3	0.92***	0.32	0.71**	0.32
HQ*Dist*Private			-0.18	0.19
HQ*Dist*JV			-1.05***	0.20
HQ*Dist*SOE			-1.19***	0.28

Notes: We control for model, county, and year fixed effects.
* p<0.1, ** p<0.05, *** p<0.01.

Home bias for models by private automakers completely disappears once we move out of the production county, suggesting that consumer ethnocentrism is extremely localized. On the other hand, home bias for JV and SOE models also drops steeply when we move out of the production counties, and continues to dissipate slowly as we move further away inside the headquarter province. However, a large part of it remains intact even at the maximum distance, where the coefficients for JV and SOE are 0.18 and 0.56, respectively. One explanation for the variation in home bias is heterogeneous degrees of local protection within the headquarter province. For example, three of the ten examples of local subsidies in Table 1 are implemented at the prefecture level, and only applicable to counties in the same prefecture as the production counties. Overall, results from

[15] Another possible explanation is county-level government protection, which is less likely since our previous results suggest no evidence for local protection for the private firms.

Table 7 suggest that while consumer ethnocentrism contributes to a large part of home bias at the production counties, its impact highly localized and almost completely diluted when we compare sales at the province level.

3.3 Falsification Tests

The spatial discontinuity design allows us to control for cluster-specific consumer preferences, dealer networks, and travel distance by focusing on neighboring counties across provincial borders. The key identification assumption is that there are no systematic differences in consumer preference toward local SOEs or JVs within the county-cluster, that is, no discontinuity in consumer preference across provincial boundaries. This could be violated if, for example, auto makers locate their headquarter in provinces that better match local consumer demographics (observed and unobserved). Although observed consumer demographics tend to be similar between neighboring counties across provincial borders, there could be differences in unobserved consumer demographics.[16] We conduct the following falsification tests to examine this assumption.

If consumers prefer local products because these products are more compatible with consumer demographics in the home province (observed and unobserved), we should find a market advantage of non-local products that are similar to local products. Our first falsification test replaces each local model with its closest non-local counterpart(s). Specifically, we group the 186 domestic models in 2011 into 68 groups of similar models. The models in each group have headquarters in two different provinces that are not adjacent, belong to firms with the same ownership type, and fall in the same vehicle segment. In addition, the models are matched on price, vehicle size, horsepower, and fuel economy. Although the last step might be subjective, the choices are often obvious as close competing products in the same vehicle segment tend to have similar attributes (for example Dongfeng-Honda Civic vs. FAW-Toyota Corolla, Dongfeng-Honda CR-V vs. FAW-Toyota RAV4).

Importantly, we swap the local status between these non-local counterparts and local products and perform the same regression discontinuity analysis as in the previous section. The coefficient estimates on the three interaction terms, HQ*private, HQ*JV, and HQ*SOE, are -0.23***, -0.04, and 0.08, compared to 0.12, 0.42*** and 0.95*** in the previous section. The results show that although consumer prefer local JVs and SOEs, they do not prefer close substitutes that are non-local. We conclude that the home bias is unlikely to be driven by the better compatibility between consumer demographics and local products, the third factor discussed in Section 3.1.

To further test on the extent of consumer preference heterogeneity across neighboring counties on provincial borders, we now turn to provinces that are not home to any auto producers. We generate 93 county clusters from these provinces following the same procedure as in Section 3.2.

[16] We are not able to find data on county-level household income from all the potential sources we know of. The sample of 2005 Census data is only representative at the prefecture (city) level.

For each cluster, we arbitrarily specify one county as the treatment group and estimate equation (2) cluster by cluster. Instead of using the three dummies of firm ownership type interacted with the local status as in the previous section, we interact ownership type with the dummy for the treatment county. If there is no systematic difference in consumer preference toward JVs or SOEs across counties within a cluster, we should expect these interaction terms to be zero. Our results confirm this: for the interaction between JV products and the treatment county, the coefficient estimate is signifiant at the 5% level for 10 out of 93 clusters (or 10.8%). For the interaction between SOEs and the treatment dummy, the coefficient estimate is significant for 5 out of 93 clusters (5.4%). The distribution of these parameter estimates centers around zero and is symmetric.

In our third falsification test, we randomly assign each automaker to one of the provinces that do not have auto firms (hence the automaker is 'local' in its assigned province), repeat this for 100 times, and estimate equation (2) for each of these 100 samples using randomly generated local status. The local SOE and JV parameter estimates center around 0, are rarely significant, and are never close to the magnitude (in *absolute value*) reported in our RD analysis across *all* of these 100 simulations. A large estimate in absolute value (either positive or negative) would indicate preference in favor of SOEs or JVs. Results here suggest that in provinces without any local SOE or JV products, we do not find any systematic evidence that they prefer SOEs or JVs over private products.

To summarize, our analysis shows a large home bias among JVs and especially SOEs, but not among private automakers. The evidence provided suggests that the home bias is not driven by transportation costs, sales network, consumer preference heterogeneity, innate preference for locally produced products, or employee discounts. The pattern of home bias is consistent with our discussion in Section 2 that local protective policies tend to be more favorable to JVs and SOEs because their importance in the local economy and the institutional connection with the local government. Together, these findings point to local protection rather than consumer preferences as the main source of home bias.

4 Structural Model

So far we have presented evidence on the existence of local protection and that it is the leading cause of home bias. In this section, we quantify its magnitude on demand for vehicles produced locally versus non-locally, taking into consideration consumer heterogeneity in auto demand. Assuming optimal pricing, these demand estimates allow us to back out cost functions for different auto producers. We first present the demand and supply models and then discuss identification and estimation strategies.

4.1 Demand

A market is defined as a province. Each year, households choose from J_{mt} models and the outside option to maximize their utility. We define the indirect utility of household i buying product j in market m and year t as a function of products attributes and household demographics:

$$u_{mtij} = \bar{u}((1-\rho_{jm})\mathrm{p}^0_{tj}, \mathrm{X}_{tj}, \xi_{mtj}, \mathrm{y}_{mti}, \mathrm{D}_{mti}) + \varepsilon_{mtij},$$

where $\bar{u}$ denotes the part of utility that is explained by product attributes and consumer demographics, and ε_{mtij} is a random taste shock which we assume to follow the type I extreme value distribution. Utility from the outside option is normalized to ε_{mti0}.

Given that local protectionism takes many forms, including explicit ones like discounts for local brands, and implicit ones such as entry barriers for non-local brands, it is impractical to incorporate formally all different forms of protection into our model. Instead, we capture them by a price discount for local brands.[17] Let p^0_{tj} denote the retail price of product j in year t, which is the same nationwide. Price with protection is denoted as $\mathrm{p}_{mtj} = (1-\rho_{jm})\mathrm{p}^0_{tj}$, where ρ_{jm} stands for the discount rate for product j in market m. In our baseline model, ρ_{jm} takes one of three values: ρ_1 if j is a JV product and m is its home market, and ρ_2 if j is an SOE product and m is its home market, and 0 otherwise.[18] We set the discount rate for private products in their home market to 0 based on evidence from our boundary discontinuity analysis. Here the degree of local protection for JV or SOE products is assumed to be the same across different provinces. Later we relax this assumption and allow the discount rates ρ_{jm} to depend on provincial attributes.

X_{tj} is a vector of observed product attributes, including a constant term, log of fuel cost, vehicle size, engine size, a dummy for automatic transmission, brand dummies, year fixed effects, and market by vehicle-segment interaction dummies. The implicit assumption of putting the vehicle attributes in logs is that additional utility diminishes as the attribute gets larger. The market by vehicle-type dummies allow market-specific taste for different vehicle types. For example, provinces with a larger average household size or hilly terrains are likely to exhibit higher preference for SUVs. ξ_{mtj} captures all unobserved product attributes, such as advertising or customer service as perceived or experienced by buyers in market m and year t. y_{mti} and D_{mti} stand for income and other household attributes.

[17] Price discounts and subsidies need to be financed by taxes. In our welfare analysis, we examine the impact of the tax-financed subsidy system on market outcomes and social welfare.

[18] We also estimate the model incorporating a separate ρ_{jm} for local private products, but the associated coefficient is small and insignificant.

We specify $\bar{u}(\mathrm{p}_{mtj}, \mathrm{X}_{tj}, \xi_{mtj}, \mathrm{y}_{mti}, \mathrm{D}_{mti})$ as

$$\bar{u}_{mtij} = -\alpha_{mti}\mathrm{p}_{mtj} + \sum_{k=1}^{K} \mathrm{X}_{tjk}\tilde{\beta}_{mtik} + \xi_j, \tag{3}$$

and define household i's marginal util from a dollar, α_{mti}, as

$$\begin{aligned} \alpha_{mti} &= e^{\bar{\alpha}_i + \alpha_1 ln y_{mti} + \sigma_p \nu_{mti}} \\ &= e^{\bar{\alpha}_i} * y^{\alpha_1} * e^{\sigma_p \nu_{mti}}, \end{aligned}$$

which has three components. The first term $e^{\bar{\alpha}_i}$ reflects the base level of price sensitivity. We allow it to take four different values, one for each of the four income brackets in the Ford survey, to better match our micro-moments. The second component y^{α_1} captures how household income influences demand sensitivity to price. One would expect α_1 to be negative since high-income households tend to be less responsive to a price increase due to diminishing marginal utility of money. Finally, we introduce a random shock $e^{\sigma_p \nu_{mti}}$, where ν_{mti} follows the standard normal distribution, and σ_p is the standard deviation of the normal distribution to be estimated. This term captures many idiosyncratic factors that influence price elasticity. Some examples include parental support, inheritance, and assets accumulated in the past. Both y_{mti} and p_{mtj} are in million yuan.

X_{tjk} stands for the kth attributes of product j. $\tilde{\beta}_{mtik}$ is the random taste by household i for attribute k due to unobserved household demographics. We define this taste as

$$\tilde{\beta}_{mtik} = \bar{\beta}_k + \sigma_k \nu_{mtik},$$

which follows a normal distribution with mean $\bar{\beta}_k$ and standard deviation σ_k. We allow random taste for the constant term, fuel cost, and engine size, in addition to price, given their importance in affecting consumer demand. Taste dispersion σ for all other attributes is assumed to be 0. The random coefficient for the constant term, ν_{mti1}, captures household i's preference for the unobserved outside option, such as existing cars or access to good public transportation. In the baseline specification, we assume that the mean taste for the vehicle attributes are equal across all markets in all years.

With all the components defined as above, the utility function can be fully written out as

$$u_{mtij} = -e^{\bar{\alpha}_i + \alpha_1 ln y_{mti} + \sigma_p \nu_{mti}} \mathrm{p}_{mtj} + \sum_{k=1}^{K} \mathrm{X}_{tjk}(\bar{\beta}_k + \sigma_k \nu_{mtik}) + \mathrm{B}_j + \zeta_m + \eta_t + \xi_{mtj} + \varepsilon_{mtij}, \tag{4}$$

where B_j, ζ_m, and η_t stand for brand, market by vehicle segment, and year fixed effects, respectively.[19]

To facilitate the discussion on identification and estimation below, we rewrite the utility function as:

$$\begin{aligned} u_{mtij} &= \delta_{mtj} + \mu_{mtij} + \varepsilon_{mtij}, \\ \delta_{mtj} &= \mathrm{X}_{tj}\bar{\beta} + \mathrm{B}_j + \zeta_m + \eta_t + \xi_{mtj}, \qquad (5) \\ \mu_{mtij} &= -e^{\bar{\alpha}_i + \alpha_1 ln y_{mti} + \sigma_p \nu_{mti}} \mathrm{p}_{mtj} + \sum_{k=1}^{K} \mathrm{X}_{tjk}\sigma_k \nu_{mtik} \qquad (6) \end{aligned}$$

where μ_{mtij}, the household-specific utility, depends on household characteristics, but δ_{mtj}, the mean utility, does not.

We use θ_1 to denote parameters in the δ_{mtj}, which we call linear parameters, and θ_2 to denote parameters in μ_{mtij}, which we call non-linear parameters, following Berry et al. (1995). The non-linear parameters include: $\theta_2 = \{\bar{\alpha}_1, \bar{\alpha}_2, \bar{\alpha}_3, \bar{\alpha}_4, \alpha_1, \rho_1, \rho_2, \sigma_p, \sigma_1, \sigma_2, \sigma_3\}$, where $\alpha_1, \bar{\alpha}_2, \bar{\alpha}_3, \bar{\alpha}_4, \alpha_1$ are price coefficients, ρ_1, ρ_2 are local protection discounts, and $\sigma_p, \sigma_1, \sigma_2, \sigma_3$ are parameters that affect the dispersion of random coefficients. The probability that household i chooses product j is:

$$\mathrm{Pr}_{mtij}(\mathrm{p}, \mathrm{X}, \xi, y_{mti}, \mathrm{D}_{mti}, \theta_1, \theta_2) = \frac{e^{\delta_{mtj}(\theta_1) + \mu_{mtij}(\theta_2)}}{1 + \sum_{h=1}^{J_m} \left(e^{\delta_{mth}(\theta_1) + \mu_{mtih}(\theta_2)}\right)}. \qquad (7)$$

The individual choice probability can then be aggregated to obtain market shares, which are matched to observed data to estimate model parameters.

4.2 Supply

We estimate the demand and supply equations separately. Our supply-side specification closely follows Berry et al. (1995) except for a few minor modifications. First, instead of choosing the optimal price in every market, a firm chooses one national price for each model that it produces to maximize its total profits in a given year. National pricing is likely a reasonable approximation for the Chinese market because market-specific promotions are rare in early years Li et al. (2015), and because arbitrage prevents large differences in prices due to the low transportation costs shipping vehicles to different regions. Second, taxes levied on automobile purchase is high in China and can account for as much as 50% of the final transaction price. This creates a sizeable wedge between the price paid by consumers and the sales revenue accrued to firms. We explicitly remove taxes

[19] We include dummies for markets interacted with three vehicle segments: Sedan, SUV, and MPV. There are $31 * 3 - 1 = 92$ dummies, and the default group is Beijing Sedan. Small/mini sedans, compact sedans, and medium/large sedans are combined into one Sedan segment, since the classification of these groups is highly correlated with size and engine displacement.

from firms' profit function. Last, many JVs in China's auto industry have common stakeholders that could facilitate implicit collusion.[20] We assume the standard Nash-Bertrand competition between firms in the baseline model, and experiment with alternative specifications that incorporate collusion among firms with a ownership structure that overlaps.

The annual national profit for firm f is (we suppress subscript t for simplicity):

$$\begin{aligned}\pi_f &= \sum_{m=1}^{\mathrm{M}} \sum_{j\in\mathscr{F}} (\mathrm{p}_j^0 - \mathrm{T}_j(\mathrm{p}_j^0) - \mathrm{mc}_j)\mathrm{M}_m \mathrm{s}_{mj} \\ &= \sum_{j\in\mathscr{F}} (\mathrm{p}_j^0 - \mathrm{T}_j(\mathrm{p}_j^0) - \mathrm{mc}_j)\mathrm{S}_j,\end{aligned}$$

where $\mathscr{F}$ is the set of all products by firm f, p_j^0 is the manufacturer suggested retail price MSRP, T_j refers to total tax and is a function of the sales price, mc_j is the marginal cost of product j, and $\mathrm{M}_m s_{mj}$ is the sales of product j in market m. In the second line, we use S_j to represent product j's national sales. Here we make two simplifying assumptions on the marginal cost. First, the marginal cost for each model is constant across all markets and does not depend on the distance between where it is produced and where it is sold. It implicitly includes the average transportation costs to different markets. Second, the marginal cost is independent of quantity and hence price.

Each firm chooses $\{\mathrm{p}_j^0, j\in\mathscr{F}\}$ to maximize its total profits. Given this assumption, p_j^0 should satisfy the following first-order condition:

$$S_j(1-\frac{\partial \mathrm{T}_j}{\partial \mathrm{p}_j^0}) + \sum_{r\in\mathscr{F}} (\mathrm{p}_r^0 - \mathrm{T}_r - \mathrm{mc}_r)\frac{\partial \mathrm{S}_r}{\partial \mathrm{p}_j^0} = 0, \forall j$$

Define Δ as a J by J matrix, whose (j,r) term is $-\frac{\partial \mathrm{S}_r}{\partial \mathrm{p}_j}$ if r and j are produced by the same firm, and 0 otherwise. The first-order conditions can now be written in vector notation as:

$$\mathrm{S}(1-\frac{\partial \mathrm{T}}{\partial \mathrm{p}^0}) - \Delta(\mathrm{p}^0 - \mathrm{T} - \mathrm{mc}) = 0,$$

which implies

$$\mathrm{p}^0 = \mathrm{mc} + \mathrm{T} + \Delta^{-1}[\mathrm{S}(1-\frac{\partial \mathrm{T}}{\partial \mathrm{p}^0})]. \tag{8}$$

In order to back out marginal costs from the equation above, we need to calculate T, $\frac{\partial \mathrm{T}}{\partial \mathrm{p}^0}$ and Δ.

A new vehicle is subjected to a maximum of four types of taxes: consumption tax (t_j^c), value-added tax (t_j^{va}), sales tax (t_j^s), and import tariffs(t_j^{im}). We use these letters to denote the tax rates. An unconventional feature of the tax system in China is that the "pre-tax" price in fact includes the

[20]The empirical evidence on collusion is mixed. For example, Hu et al. (2014) rejects hypotheses of collusion.

consumption tax, which depends on the engine size of the vehicle. For example, if the pre-tax price of a vehicle is 100k yuan and consumption tax is 25%, the firm gets 75k yuan from each unit of the vehicle sold, while the government collects the remaining 25k as consumption tax. The other three types of taxes are charged as a percentage of the pre-tax price. Valued-added tax is 17% for all models, import tariff is 25% for imported products, while sales tax is normally set at 10% but had been lowered to 5% and 7.5% for vehicles with engine displacement no more than 1.6 liters in 2009 and 2010, respectively. Let p_j^0 denote the retail price paid by consumers, and p_j^f denote firm's revenue. We have:

$$\begin{aligned}
\mathrm{p}_j^0 &= \frac{\mathrm{p}_j^f}{1-t_j^c} * (1+t_j^{va}+t_j^s+t_j^{im}), \\
\mathrm{T}_j &= \mathrm{p}_j^0 - \mathrm{p}_j^f = \mathrm{p}_j^0 - \frac{\mathrm{p}_j^0 * (1-t_j^c)}{1+t_j^{va}+t_j^s+t_j^{im}}, \text{ and} \\
\frac{\partial \mathrm{T}_j}{\partial \mathrm{p}_j^0} &= 1 - \frac{1-t_j^c}{1+t_j^{va}+t_j^s+t_j^{im}}
\end{aligned}$$

To calculate Δ, note that the impact of a price change on the total sales is the sum of the impacts across all individual markets. We write

$$\begin{aligned}
\frac{\partial \mathrm{S}_j}{\partial \mathrm{p}_j} &= \frac{\partial \sum_{j=1}^{31} \mathrm{S}_{mj}}{\partial \mathrm{p}_j} = \sum_{m=1}^{31} \mathrm{M}_m \frac{\partial s_{mj}}{\partial \mathrm{p}_j} = \sum_{m=1}^{31} \mathrm{M}_m \frac{\sum_{i=1}^{1000} \frac{\partial s_{mij}}{\partial \mathrm{p}_j}}{1000} \\
&= \sum_{m=1}^{31} \mathrm{M}_m \frac{\sum_{i=1}^{1000} -\alpha_{im} s_{mij}(1-s_{mij})(1-\rho_{jm})}{1000}.
\end{aligned}$$

where we simulate 1,000 individuals in each market to calculate market shares ($i = 1, ..., 1000$). Similarly, we have:

$$\frac{\partial \mathrm{S}_r}{\partial \mathrm{p}_j} = \sum_{m=1}^{31} \mathrm{M}_m \frac{\sum_{i=1}^{1000} \alpha_{im} s_{mij} s_{mik} (1-\rho_{mj})}{1000}.$$

With the three components solved for, we can now back out marginal cost for each model j. Marginal cost is assumed to be constant across all markets, and does not depend on quantity:

$$\mathrm{mc}_{tj} = W_{tj}\phi + \omega_{tj}, \tag{9}$$

where W_{tj} include vehicle attributes, firm-type dummies, and year dummies, and ω_{tj} stands for unobserved cost shock to model j in year t. We are most interested in the coefficients of firm-type dummies, which capture the relative cost efficiency among private firms, SOEs, JVs, and imports.

4.3 Identification and Estimation

Our discussion of identification focuses on two sets of key parameters: a) the price discounts ρ_1 and ρ_2 that capture the extent of local protectionism, and b) the coefficients that capture consumer price sensitivity. We then briefly describe how parameters are estimated.

Since we do not observe local protection directly, the key to quantify the extent of local protectionism is to control for the confounding factors, including transportation costs, market access, and consumer preference (due to observed and unobserved demographics or innate preference for local products). The analysis from the spatial discontinuity design suggests that these are not the major drivers behind the home bias pattern observed in the data. In the structural model, we control for transportation costs using the distance between the market and the location of production and control for market access using the number of dealers by province by brand. In addition, we include province-vehicle segment fixed effects to control for market-specific preference for different vehicle types. Similar to the findings from the spatial discontinuity design, the coefficient estimate on the price discount that captures local protectionism does not vary substantially across specification with different controls of these variables.

To address the price endogeneity arising from the correlation between prices and unobserved product attributes ξ_{mtj}, we use excluded instruments that include the number of products in the same vehicle segment by the same firm, the number of products in the same vehicle segment by rival firms, and the consumption tax. Non-price attributes serve as instruments for themselves and are assumed to be orthogenal to the unobserved attributes. The first two variables – number of own or rival products – are in the spirit of traditional BLP IV: they capture the intensity of competition and should affect the pricing decision.

The third IV, the consumption tax, is motivated by the fact that tax rates vary by vehicle engine size. The rational for these tax policies is to promote sales of small and fuel-efficient vehicles to reduce pollution and congestion. The tax rates range from 1% for engine size equal to or smaller than 1.0L to 40% for engine size above 4.0L. Since engine size is positively correlated with price (cars with larger engines tend to be more expensive), this tax scheme introduces discrete jumps in prices at the boundaries of engine size brackets. We further add separate home market dummies for JVs and SOEs to the list of instruments.

Consumer price sensitivity is captured by $e^{\bar{\alpha}_i+\alpha_1 lny_{mti}+\sigma_p v_{mti}}$ as shown in equation (4). To better match with the micro level data described in table 4, we allow the base level of price sensitivity, $e^{\bar{\alpha}_i}$, to take four different values $\{e^{\bar{\alpha}_1}, e^{\bar{\alpha}_2}, e^{\bar{\alpha}_3}, e^{\bar{\alpha}_4}\}$, corresponding to the four income brackets in the Ford Survey. Two data patterns help to identify these coefficients. The first one is the variation in market shares: more expensive models have higher market shares in provinces with higher household income. This helps to identify the income coefficient α_1. The second and more powerful source of identification is the micro-moments: households with higher income are more likely to buy new vehicles, and much more likely to buy expensive vehicles such as large sedans and SUVs than low-income households. These moments help to identify $\{\bar{\alpha}_1, \bar{\alpha}_2, \bar{\alpha}_3, \bar{\alpha}_4\}$. A high $\bar{\alpha}_i$ makes all consumers in income group i dislike price more and less likely to buy new vehicles. If the estimated coefficient leads to an over-prediction of the fraction of consumers from income group i, $\bar{\alpha}_i$ will increase until the model's prediction aligns with the level observed in our micro-moments.

Demand-side parameters are estimated by simulated GMM with two sets of moment conditions. The first set of moment conditions is constructed using excluded instruments and exogenous vehicle attributes that are discussed above, as well as a dummy for local JV products and a dummy for local SOE products.[21] The second set of moment conditions are based on the Ford survey of new vehicle buyers. They require the model predicted fractions of buyers in each income bracket to match the observed shares for each of the three years in the survey, both across all vehicle segments and separately for each of the four vehicle segments. There are 45 micro-moments and 181 macro moments, or 226 moments altogether.[22]

The estimation is carried out in simulated GMM with a nested contraction mapping as is now standard in the BLP literature.[23] The estimation of parameters is carried out in a two-step procedure: we start with identity matrices as the weighting matrix to obtain consistent estimates of the parameters and the optimal weighting matrix; then we re-estimate the model with the optimal weighting matrix to obtain the final parameter estimates.

5 Estimation Results

5.1 Demand

Table 8 shows estimation results from two specifications of the random coefficient model. In both specifications, the linear parameters are those in the mean utility defined in equation (5) and the price coefficients and random coefficients are in the household-specific utility defined in equation (6). Column (1) requires all income brackets to have the same base level price sensitivity $e^{\bar{\alpha}}$. Column (2) allows each income group i to have a distinct $e^{\bar{\alpha}_i}$, which helps us to match the micro

[21] We assume that headquarter locations are exogenous and orthogonal to contemporaneous variation in product quality ξ_{mtj}.

[22] For micro-moments, we have four income brackets, five segments as well as all segments combined, and three years, which leads to $3 * 5 * 3 = 45$ micro-moments. Note that we do not include moments associated with the fifth vehicle segment (MPV) because the fraction of buyers in each income group for MPV is linearly dependent from those for the other segments and across all vehicle segments. For macro moments, we have 6 excluded IVs, which are the number of own and rival products in the same segment, consumption tax rate and level, dummy for SOE and JV; 7 product attributes, 92 province by vehicle type dummies, 2 year fixed effects, 1 dummy for Beijing 2011 lottery policy that reduces car demand, and 73 brand dummies.

[23] The simulation is based on 1000 Halton draws in each province. The convergence criterion for the contraction mapping is 1e-13.

moments.

Table 8: Results from the RC model

	(1) One $\bar{\alpha}$		(2) Four $\bar{\alpha}$s	
	Est.	S.E.	Est.	S.E
Linear parameters				
log(Fuel cost)	-1.72***	0.39	-1.17***	0.32
log(Displacement)	4.45***	0.45	4.34***	0.46
log(Size)	8.65***	0.60	9.11***	0.53
Auto Transmission	0.87***	0.32	0.89***	0.33
Distance to headquarter	-0.08***	0.02	-0.10***	0.02
Number of dealers	0.01***	0.00	0.01***	0.00
Price coefficients				
$e^{\bar{\alpha}_1}$ ($e^{\bar{\alpha}}$)	1.77***	0.20	0.06***	0.02
$e^{\bar{\alpha}_2}$			0.20***	0.04
$e^{\bar{\alpha}_3}$			0.15***	0.03
$e^{\bar{\alpha}_4}$			0.61***	0.09
α_1	-1.92***	0.21	-3.15***	0.32
JV discount, ρ_1	0.11***	0.02	0.11***	0.02
SOE discount, ρ_2	0.28***	0.03	0.28***	0.03
Random coefficients				
Constant, σ_1	2.59***	0.50	3.10***	0.56
log(Fuel cost), σ_2	1.71***	0.19	1.25***	0.13
log(displacement), σ_3	0.96	0.77	1.44	0.84
price, σ_p	1.18***	0.10	1.43***	0.08

Note: The number of observations: is 19,505. * p<0.1, ** p<0.05, *** p<0.01

All linear parameter estimates are intuitively signed and statistically significant in both specifications. The first four estimates measure consumer preference for product attributes: consumers dislike vehicles with higher fuel costs but prefer larger and more powerful vehicles and vehicles with automatic transmission, all else equal. Our estimates predict that an 10% increase in fuel cost reduces sales by around 10.6%, while a 10% increase in displacement and vehicle size increases sales by around 51.2% and 138.3%, respectively. All else equal, conversion to manual to automatic transmission increases sales by around 143.5%. Distance to headquarter and the number of dealers control for transportation costs and dealer network. Their coefficient estimates in both specifications suggest that an additional dealer store in the province increases sales by around 1% (the average number of dealers is 21), and that sales decrease by about 9.5% for every 1000km further away from a model's headquarter province, both being quantitatively significant.

Perhaps not surprisingly, the second specification delivers a much better fit of the micro-moments, as documented in Table 9. The largest prediction error is 3.1%, and the average prediction error is only 1.4%. The fit for the segment-specific income shares is also decent. In contrast, the first specification under-predicts fractions of buyers in the first and third income brackets by a big margin, partly because the functional form of income $y_{mti}^{\alpha_1}$ in the price coefficient does not allow enough flexibility in the curvature. In the discussion that follows, we use coefficient estimates from the second specification.

Table 9: Model Fit in Micro-moments

year	Income group	observed share	Predicted share Specification (1)	Predicted share Specification (2)
2009	<48k	15.8%	12.9%	16.9%
	48k-96k	33.6%	43.1%	31.6%
	96k-144k	32.0%	18.1%	28.9%
2010	<48k	10.9%	10.3%	12.3%
	48k-96k	26.9%	35.9%	27.3%
	96k-144k	33.3%	26.3%	35.8%
2011	<48k	9.3%	7.3%	8.6%
	48k-96k	26.2%	33.6%	27.6%
	96k-144k	33.7%	27.4%	33.3%

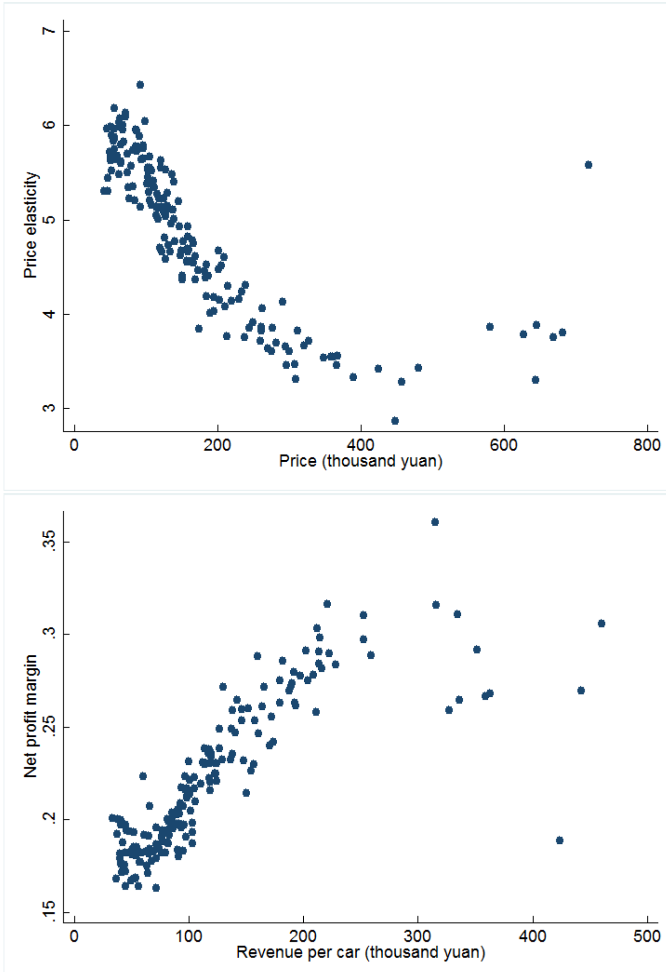
Notes: We drop the highest income bracket from each year. The parameter estimates for specifications (1) and (2) are presented in Table 8.

Our estimate of α_1 (-3.15) in specification (2) suggests that income is a strong predictor of vehicle demand, as shown from household surveys in Table 4. When income doubles, disutility from price shrinks quickly. Consider a car priced at 140k yuan, the median price in our sample in 2011. The average demand elasticity is -1063.3, -111.2, -16.7 and -4.2 when an individual's income is $24k$, $72k$, $120k$ and $288k$, respectively.[24] Low-income households have little accumulated wealth and limited access to bank loans and are very unlikely to purchase new vehicles. Our model predicts that most vehicles are purchased by high-income households, which is consistent with the Ford survey.

On the other hand, at any given income level, there is a large dispersion in disutility of price, as indicated by our estimate of σ_{p}, $\hat{\sigma}_{\text{p}} = 1.43$. Consider two consumers with the same income ($y_{mt1} = y_{mt2} = 0.12$ mill Yuan) but different draws of the random price sensitivity component ($\nu_{mt1}^{p} = 1$, and $\nu_{mt2}^{p} = -1$). Our model predicts that for a car priced at 140k yuan, demand elasticity is -69.8 and -4.0 for those two individuals, respectively. The large dispersion in price sensitivity for a given income level is necessary to fit the data pattern that some expensive models have substantial sales in provinces with relatively few high-income households.

[24]Income is in millions of yuan in our estimation, or $y_{mti} = 0.048, 0.144, 0.3$ for this example.

Figure 4: Price Elasticities and Markup-Price Ratios



To help understand the magnitude of the parameter estimates, we plot the 2011 own-price elasticities and Lerner index against vehicle price for each model in Figure 4. Own price elasticity varies from -2.67 to -7.14, with a median of -4.88. Models with a higher price tend to have a lower elasticity as shown in the top panel of Figure 4.[25] The magnitudes of the own price elasticities are somewhat larger than those obtained for the U.S automobile market in Berry et al. (1995) and Petrin (2002). Chinese vehicle buyers have lower average income than those in U.S. and hence are likely to be more price sensitive.[26] The bottom panel of Figure 4 depicts the Lerner index using

[25]Everything else equal (for example, fixing individuals' observed and unobserved preference), more expensive models have more elastic demand by construction. On the other hand, expensive models are typically purchased by wealthy individuals who are less price sensitive, which is captured by the income variable in our price coefficient $y_{mti}^{\alpha_1}$. However, the income distribution we use is bounded above and capped at the maximum income observed in our 2005 Census. For the ultra-expensive models that are priced above 600,000 RMB ($90,000), the upper bound of income becomes binding and the elasticity starts to increase after a certain point.

[26]As discussed in Section 2, brands produced by joint ventures and imports are one to three times more expansive in China than in U.S..

before-tax prices. The ratio varies from 16.3% to 36.0%, with a mean of 22.2%. Products with a high price have a large Lerner index as buyers of those expensive automobiles tend to be less price sensitive.

Estimates of ρ_1 and ρ_2 suggest that the price discount implied by local protectionism is equivalent to 11% of MSRP for local JV products and 28% for local SOE products. Some of the reported direct subsidies in Table 1 are as high as 15% of the auto price for local brands. Besides direct reduction in the purchasing price, subsidies come in other forms including waivers of registration fees and tolls and low-interest loans. There are also other implicit barriers to market access. Our estimates of price discounts encapsulate the impact of all forms of local protectionism.

These very significant discounts, together with variation in products' own-price elasticites, are consistent with the magnitude of home bias for JV and SOE products estimated via the regression discontinuity design in Table 5. For example, a 11% price discount for JVs and a price elasticity of -4.88 would imply roughly a 54% increase in sales, compared to 49% estimated in Table 5. In the baseline specification, we normalize the price discount toward products by private automakers to zero based on the empirical evidence of no economically significant home bias for these products. In an alternative specification, we incorporate a separate price discount for local private products. The wedge between the coefficient of local private products and local JVs and SOEs remains the same. If we interpret the (modest) coefficient of local private products as capturing the usual home-bias arising from preference (e.g., patriotism), then our results indicate that local protectionism appears much more important than local preference in affecting demand for local JV and SOE products.

5.2 Supply

Once we obtain demand parameters, we use the optimal pricing equation (8) to back out marginal costs, taken into consideration the impact of the tax schedules and different ownership structures across firms. Here we assume Bertrand-Nash pricing with no collusion. We also estimate marginal costs assuming that firms partially internalize interests of other firms with common ownership, as in Jie et al. (2013) and Miller and Weinberg (2016). For example, FAW-Toyota and Tianjin-Toyota share a common foreign partner, which might soften the price competition between these firms. RESULTS TO BE ADDED.

To examine how car attributes and firm type affect marginal costs, we regress log of marginal costs on these controls (see equation (9) for the marginal cost equation). There are 631 observations in total, one for each model-year, since prices are set at the national level. Table 10 presents results for the base specification, with marginal cost being constant in quantity and assuming no collusion. Column (1) includes the key attributes and their squared terms, and a separate dummy for vehicle segment SUV and MPV. Column (2) adds brand fixed effects. Column (3) further includes estimated $\hat{\xi_{mtj}}$ from the demand-side to control for unobserved product quality. We average $\hat{\xi_{mtj}}$ across provinces to obtain the national average. In Column (4) and (5), we break down JV products by the origin of the foreign partner (Column (4)), and add a control for labor cost at the plant location (Column (5)).[27]

The coefficients on car attributes are in general intuitive. For example, marginal costs are higher for larger engine size, larger cars, cars with auto transmission, and SUVs. Multi-purpose vehicle segment includes a variety of specialized cars, including mini-buses that are often of lower quality with lower prices. Their marginal cost is lower than that for the other two segments. The only exception is the coefficient for fuel costs. The positive coefficient on fuel use implies that it is cheaper to produce more fuel efficient cars, which is somewhat puzzling. This might be driven by the high correlation between fuel use, engine size, and size.

Turning to the relative cost efficiency among private, SOE, JV, and foreign auto makers, results from Column (1) suggest that private firms and SOEs enjoy 25% to 34% cost advantage over JVs (the base group) and a similar advantage over imports. This is mostly driven by different product mix between private/SOE and JV/foreign firms. Compared with domestic auto firms, JVs and foreign firms produce more high-end products (leather seats, sunroof, etc.) that are more likely to use high quality parts. Once we control for brand fixed effects (Column (2) onward), the gap in marginal costs reduces by a large margin. Private firms are the most cost efficient among the four groups, and their marginal cost is about 5-6% lower than that of JVs across different specifications. Imports are the close runner-up, with a 4-5% of cost advantage.

Surprisingly, JVs do not seem to be more cost efficient than SOEs, even though all foreign partners are well-known leading auto producers in the world. When we separate JVs by the country origin of their foreign partners, we find that JVs with US, Japanese and Korea partners have similar cost efficiency to the SOEs. JVs with European partners appear the least efficient, and their marginal cost is 9% higher than that of domestic private auto firms.

The fact that JVs do not appear more efficient than SOEs might be related to how they are managed. First, every domestic partner of a JV is an SOE in our sample period.[28] Second, these SOE domestic partners hold at least 50% stake in a JV and in most cases control the operation and management of the firm, while the foreign partner mainly provides the technology.

[27] Wages for automakers at the city level are difficult to find. Instead, we use each city's median urban household income divided by the average household size from the 2005 Census as a proxy for auto-workers' wage. For imports, we use the maximum of our constructed city-level 'wage', since wages for auto-workers in Europe, U.S.A., or Japan/South Korea are much higher than those in China.

[28] The only private firm that formed a joint venture with foreign producers in our sample is Youngman Lotus, but it had negligible sales and ceased passenger car production in 2015 and was dropped in our estimation. The first joint venture between a prominent private and a foreign auto producer happened in 2010, when BYD and Mercedes-Benz formed a joint venture BYD Daimler. Their first production debuted in 2014.

The medium marginal cost of a JV product in our sample is around 100k yuan. The transfer of vehicle production from JVs to private firms would lead to a cost saving of about 6%, or around 6k yuan per vehicle.

Table 10: Results from cost-side estimations

	(1)		(2)		(3)		(4)		(5)	
	Est.	S.E.	Est.	S.E	Est.	S.E	Est.	S.E	Est.	S.E
Private	-0.08***	0.03	-0.04***	0.02	-0.04**	0.02	-0.04*	0.02	-0.04**	0.02
JV/JV(US)	0.25***	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.02
JV(Japan)							-0.00	0.02	-0.00	0.02
JV(Korea)							0.03	0.02	0.03	0.02
JV(Europe)							0.06***	0.02	0.06**	0.02
Imports	0.33***	0.04	-0.02	0.03	-0.02	0.03	-0.02	0.02	-0.04	0.03
Fuel use^2	-0.01	0.00	-0.01**	0.00	-0.01**	0.00	-0.01**	0.00	-0.01**	0.00
Engine size	1.38***	0.16	0.71***	0.11	0.67***	0.10	0.71***	0.10	0.70***	0.10
Engine size^2	-0.17***	0.03	-0.08***	0.02	-0.07***	0.02	-0.07***	0.02	-0.07***	0.02
Size	-0.33***	0.11	0.07	0.07	0.15**	0.06	0.13**	0.06	0.13**	0.06
Size^2	0.03***	0.01	0.00	0.00	-0.00	0.04	-0.00	0.00	-0.00	0.00
Auto Trans.	0.18***	0.02	0.12***	0.01	0.12***	0.01	0.12***	0.01	0.12***	0.01
SUV	0.04	0.03	0.09***	0.02	0.08***	0.02	0.09***	0.02	0.09***	0.02
MPV	-0.06*	0.03	-0.05**	0.02	-0.05**	0.02	-0.04**	0.02	-0.04**	0.02
ln(labor cost)									0.14	0.12
year FE	Y		Y		Y		Y		Y	
Brand FE	N		Y		Y		Y		Y	
$\bar{\xi}$	N		N		Y		Y		Y	

Note: The number of observations is 631. The reference firm type is JV in Columns (1) to (3), and JV(US) in Columns (4) and (5). Brand fixed effects and $\bar{\xi}$ are from the demand estimation. *p<0.1, ** p<0.05, *** p<0.01.

6 Simulations and Welfare Analysis

We examine what would happen in terms of market outcomes and social welfare if the trade barriers across regions are eliminated. We conduct simulations based on 2011 to illustrate the results.

6.1 Impacts on Market Outcomes

We first predict vehicle sales setting the discount rates ρ_1 and ρ_2 to zero to mimic a world without local protectionism. The top panel of Table 11 demonstrates that SOE products would lose three quarters of the sales in their headquarter (home-market) province, while JV products lose about one third of their home-market sales. In contrast, the impact of removing local protection on national vehicle sales is much smaller: in the absence of any price adjustment, the national market share reduces by 4.1% for SOEs and 0.8% for JVs. Relative to free trade, local protection increases

SOEs' and JVs' national sales by a modest margin. This occurs for two reasons. First, there are 31 provinces in China and each firm has only one home market. As a result, home-market sales, which directly benefit from local protection, only account for 5% of national vehicle sales for the median vehicle. Second, when all provinces implement local protection, a SOE or JV auto-marker benefits in its home province but loses in other provinces. This kind of business-stealing offsets the effectiveness of local protection in increasing national demand for locally protected products. In theory, higher local demand could be entirely offset by lower sales elsewhere, as in the classic example of prisoners' dilemma. In our setting, the local benefit on average outweighs the losses elsewhere, though there is considerable heterogeneity among different vehicle models.

When we remove local protection, a significant fraction of sales lost by these protected local products goes to similar non-local products, rather than the outside option. This kind of substitution leads to a 3.0% increase in national sales of private brands, and a 0.8% increase for imported brands. Consumers who switch away from a local SOE or JV product tend to be more price sensitive and and are unlikely to substitute towards expensive imported products. Private brands benefits the most because their prices are on average lower than other products and they have similar attributes to the heavily protected SOE brands.

If price discounts were to be removed as a correction of existing policies, firms would adjust prices to cope with the loss of their home biass. The bottom panel of Table 11 reports changes in sales when prices are allowed to change and Figure 5 plots the distribution of price updates by firm types.[29] The magnitudes of the average price adjustments are small since removing local protection only has limited impacts on national vehicle demand. The majority of the JV and SOE products would see price cuts due to significant demand loss in the home market.

The magnitude of the price adjustment is highly correlated with the importance of the home market. For example, the largest price reductions (-1.71% and -2.38%) come from two models produced by Xiali, whose home-market sales account for around 20% of their national sales, relative to the medium model whose home-market sales account for 5% of its national sales. In addition, products with a small home market may experience a gain in their national sales and report a price increase as a result.

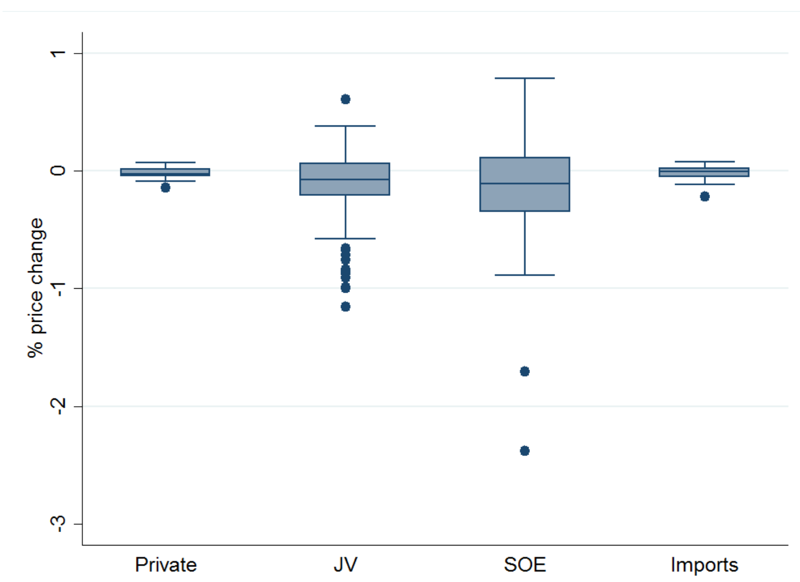
[29]For each year, we numerically solve a system of J non-linear equations following the optimal pricing equation in page 21. J is the number of models in that year.

Table 11: Impacts of Removing Local Protection on Sales in 2011

Firm type	Home-market Sales ('000)			National Sales ('000)		
	Before	After	% Change	Before	After	% Change
Without price updates						
Private	74	76	2.6%	967	996	3.0%
JV	426	294	-31.1%	6232	6184	-0.8%
SOE	105	25	-76.4%	1277	1224	-4.1%
Imports				357	360	0.8%
With price updates						
Private	74	76	2.2%	967	988	2.1%
JV	426	295	-30.7%	6232	6190	-0.7%
SOE	105	26	-75.4%	1277	1244	-2.6%
Imports				357	359	0.6%

Compared to SOE and JV products, the price adjustments for private and imported products are smaller in absolute value, which is driven by two opposing forces. On one hand, the removal of local protectionism increases demand for these products, exerting upward pressure on prices. On the other hand, prices are strategic substitutes. When SOEs and JVs reduce their prices, it exerts downward pressure on prices of private and imported cars. Note that in our setting with multi-product firms and price discounts that are local in nature, patterns of price adjustments are more complex than that of a single-product firm in a national market.

Figure 5: Percentage Price Changes by Firm Type



Overall, the removal of local protectionism leads to a price reduction for the majority of the products while the decreases are larger for JV and SOE products than for products from private and foreign automakers. As shown in the bottom panel of Table 11, these price changes help to counteract part of the reduction in sales when local protection is absent.

6.2 Welfare Analysis

We now examine the welfare consequences of local protectionism separately for consumer surplus, firm profits, and tax revenue. The removal of local protection increases consumer welfare through two channels. First, the simulations above demonstrate that the majority of the vehicle models would see price cuts absent local protectionism. Second, local protection distorts consumer choices toward SOE or JV products that can be suboptimal. Eliminating local protection gets rid of such choice distortions and increases welfare.

To illustrate the welfare loss of choice distortions, consider a simple example where consumer i in market m obtains a consumer surplus of 10,000 yuan from her top choice product A, and a surplus of 6000 yuan from a local product B. Suppose that the government in market m provides a subsidy of 5000 yuan to consumers who purchase B. The subsidy leads consumer i to choose B over A, which entails a welfare loss of 4000 yuan: the government spends 5000 yuan subsiding consumer i's vehicle purchase, but only increases her surplus by 1000 yuan. We incur such losses whenever local protection causes a consumer to choose a suboptimal local brand that is different from her intrinsic top choice. Importantly, the magnitude of the welfare loss is solely determined by the gap in the intrinsic utility between a consumer's top choice and the subsidized product, and is *independent* of the size of subsidy.

To compare consumer surplus with and without subsidies, we use simulations. For each province, we draw 1,000 pseudo consumers using the empirical income distribution and 20,000 random ε_i vectors for each consumer. Then we calculate the monetized difference in the intrinsic utility between a consumer's top choice without protection and with protection. The intrinsic utility of the top choice without protection is:

$$\text{Max Utility} = \max_{j=0,\ldots,J} \{\bar{u}^1_{ijm} + \varepsilon_{ijm}\} \tag{10}$$

where $\bar{u}^1_{ijm}$ is the same as that defined in equation (3) but excludes the price discounts for local JVs and SOEs. The intrinsic utility of the best choice under protection is:

$$\text{Max Utility}^{\text{Protection}} = \max_{j=0,\ldots,J} \{\bar{u}_{ijm} + \varepsilon_{ijm}\} - \rho_{kmt} p^0_{kmt}|_{k=argmax_{j=0,\ldots,J}\{\bar{u}_{ijm}+\varepsilon_{ijm}\}} \tag{11}$$

where $\bar{u}_{ijm}$ is the same as that defined in equation (3), k is the top choice under local protection, and $\rho_{kmt} p^0_{kmt}$ is the subsidy (price discount) associated with choice k. The difference between

(10) and (11), averaged across ε_i draws and divided by α_{mti} (consumer i's price sensitivity), is the welfare loss associated with choice distortions for consumer i. We average the welfare loss across consumers and multiply it with the market size to obtain the total welfare loss in market m under local protection. Then we aggregate it to the national level to obtain the welfare gain from removing local protection nationwide.

Note that not all local protection is equated as monetary price discounts. One might be concerned that this could overstate the loss of protection since local protection comes in many forms, and not all of them involve monetary subsidy. Fortunately, whether local protection involves monetary subsidy is irrelevant for the calculation here, since the magnitude of the welfare loss of choice distortions only depends on the gap of the *intrinsic* utility between a consumer's top choice and the subsidized product.

Figure 6: Consumer welfare gains through removing local protection (bn. yuan), 2011

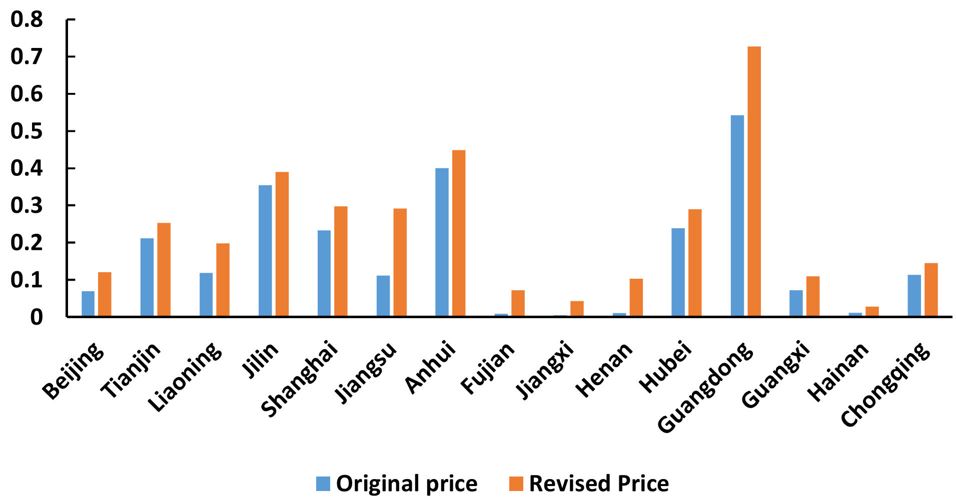


Figure 6 shows predicted consumer welfare gains in 2011 by provinces when choice distortion is eliminated. The blue bars show welfare gains from choice elimination only, while the orange bars include additional welfare gains after firms update their prices.[30] As expected, welfare gain is higher in larger markets such as Guangdong, and in provinces that house more native JV and especially SOE brands. For example, Anhui only account for 2.9% of total vehicle sales in China in 2011, ranked 13 out of the 31 provinces. However, it records the second highest expected welfare gains since it is the home to two of the largest SOE brands, Chery and JAC.

Our simulations show that consumer welfare gain from the elimination of choice distortions is 2.5 billion yuan, or roughly 22% of total subsidies in 2011. Allowing prices to adjust further leads to an additional welfare gain of one billion yuan. Over the three-year period, total expected welfare

[30]The graph only shows 14 provinces that have at least one native JV or SOE brands. The other 17 provinces mainly benefit from price reductions.

gain from the elimination of local protection is 12.3 billion yuan (nearly $2 billion), or 36.7% of total subsidies for local products.

While local protectionism reduces consumer welfare shown above, Table 12 presents its impact on firm profit and tax revenue. Removing local protection reduces the profits of, and the tax revenue from, JVs and SOEs while benefits private automakers and imports. The elimination of the subsidies to local JVs and SOEs would lead some consumers to switch to products from private and foreign automakers, as well as the outside good. The simulation results illustrate that the removal of local protection would lead to a reduction of 2.9 and 2.6 billion yuan in firm profit and tax revenue in 2011, respectively.

Table 12: Impacts of Removing Local Protection on Profits and Tax in 2011

Firm type	Total Profit (bill.)			Tax Revenue (bill.)		
	Before	After	% Change	Before	After	% Change
Without price updates						
Private	10.3	10.6	2.8%	17.2	17.7	2.7%
JV	223.5	221.7	-0.8%	297.9	295.3	-0.8%
SOE	17.4	16.8	-3.5%	27.1	26.1	-3.6%
Imports	27.6	27.8	0.8%	62.2	62.7	0.7%
With price updates						
Private	10.3	10.5	2.0%	17.2	17.6	2.0%
JV	223.5	221.1	-1.1%	297.9	295.6	-0.8%
SOE	17.4	16.7	-4.0%	27.1	26.2	-3.2%
Imports	27.6	27.7	0.5%	62.2	62.6	0.5%

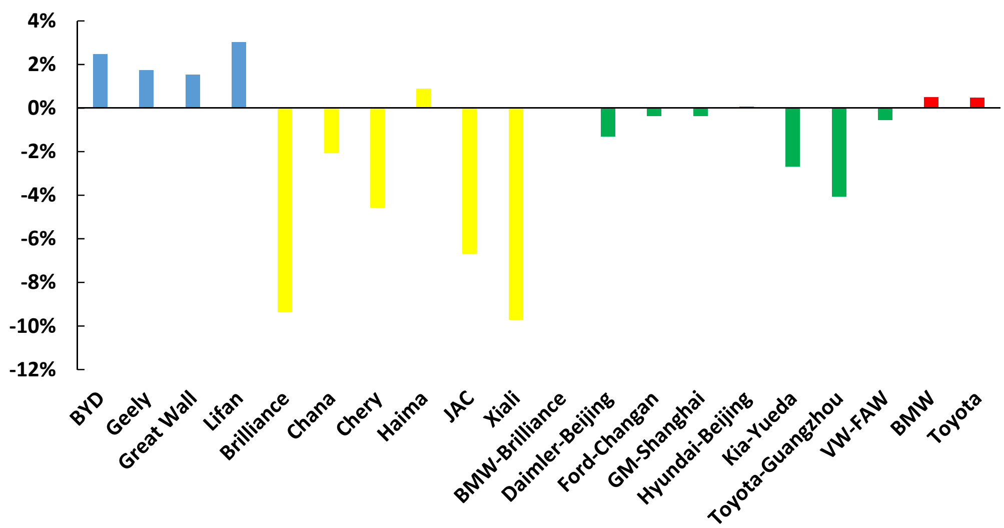
Notes: The unit for profit and tax revenue is billion yuan.

Figure 7 shows the impact of removing local protection on firm profit for selected firms of different ownership type (the first four are private automakers; the next six are SOEs; the six after that are JVs; and the last two are imports). Consistent with the table above, local protection generally benefits JVs and SOEs at the expense of private automakers and imports. Nevertheless, there is some heterogeneity across firms even within the same ownership type. Among SOEs, Brillance and Xiali enjoy a very large benefit from local protection while Haima suffers from local protective policies. This heterogeneity is driven by the fact that local protection is a double-edged sword in that it benefits the firm in the local market but it hurts the firm in non-local markets. If the product is unpopular in the local market[31](such is the case for BMW-Brilliance) or the local market is too small (such is the case for Haima) for example due to poor compatibility with the local market demographics, the net impact of the local protection could be negative. On the other hand, Bril-

[31]One reason for this to happen is that a product may be a poor match for the population demographics in its home market. For example, BMW-Brilliance sells high-end products that are unaffordable for most consumers in its home market Liaoning.

liance and Xiali are very popular brand in the local market but fairs poorly in non-local market (for example due to poor reputation in the those markets). Local protection can benefit these brands locally much more than it hurts them in non-local markets.

Figure 7: Impact on Firm Profit by Firm Type



A significant portion of the profit and tax revenue loss arises from consumers switching away from the once-protected local brands to the outside option. One needs to be careful in interpreting these loss as net 'welfare loss', as it is more appropriate to view them as a redistribution across different industries. Our supply side is a partial analysis and does not model the profit and tax revenue associated with the outside good (or the spending on other types of goods). When consumers switch to the outside option, they are likely to spend on public transportation, used cars, or other economic activities that would generate profits and tax revenue elsewhere. While the reduction of local car production would indeed hurt the auto industry (or more specifically, most JV and SOE automakers), its economy-wide impact on industry profits and tax revenues is ambiguous and beyond the scope of our analysis.

The tangible part of welfare impact on the firm side is driven by substitution across products. For example, the removal of local protection could lead to larger sales of more or less profitable products. To examine this, we use numeric simulations to separate substitutions among different car products from substitutions to the outside option.[32] Our results show that in 2011 JVs and SOEs would lose 33,542 and 20,157 units of sales to the outside option, corresponding to a net profit loss of 1.1 billion and a tax revenue loss of 1.6 billion. The remainder of 1.8 and 1.0 billion in profit

[32]For every pseudo household in each market with a native JV or SOE brand, we draw 20,000 vectors of ε_i, each of which pins down household i's top choice with and without local protection. We then average the substitution patterns over 20,000 draws to obtain substitution patterns by household i, and average over the 1000 pseudo households to replicate substitution patterns in each market.

and revenue loss comes from substitutions across products in two ways. First, JVs and SOEs lose 20,298 units to private product and 2271 units to imports.[33]. Private firms typically have charge lower prices, thinner profit margins, and pay lower taxes. The medium profit margin is around 10k, 25k, 11k, 73k per vehicle for private, JV, SOE, and imported brands, respectively. Second, majority of the substitutions happen between products under the same type of firm. In 2011, JVs and SOE lose 94,266 and 39,035 units of sales each to other JVs and SOEs. When consumers switch away from a local product after the removal of subsidies, they are more likely to choose cheaper products that fetch lower profit margin and pay less tax. During the three-year period, total profit and tax revenue loss from substitution across products is 4.9 billion yuan and 3.1 billion yuan, respectively.

So far we have ignored the fact that tax collection is necessary to finance government subsidies and that the marginal excess burden per additional dollar of tax revenue is non-trivial. According to Ballard et al. (1985), the welfare loss from a 1 percent increase in all distortionary tax rates is in the range of 17 to 56 cents per dollar of extra revenue in the U.S., using elasticity assumptions that appear plausible. There are many reasons to believe that the marginal excess burden for tax collection is higher in China, since taxed activities are likely to be more elastic, market distortions are more severe, and tax evasion is prevalent. The total amount of tax subsidy is estimated to be 34 billion Yuan during our sample period. Assuming the marginal excess burden is 37 cents per Yuan (37%) using the mid point of the estimates provided by Ballard et al. (1985), the welfare loss associated with the tax collection to finance subsidies amounts to 12.58 billion Yuan. Even if the actual monetary subsidy is half of our estimates (which captures implicit barriers in addition to direct subsidies), the welfare loss associated with tax collection is still substantial.

Overall, our results suggest that the removal of local protection would induce more intense price competition and improve consumer surplus by 12.3 billion yuan through eliminating choice distortions. At the same time, it would lead to a total loss of 8.0 billion yuan in profits and tax revenues as sales accrue to less profitable firms. Our cost-side estimates suggest that private firms are more cost-efficient than SOEs and JVs by around 5%. While the magnitude of such cost-savings is small in the short-run, eliminating local protection would benefit the growth of private firms, which in turn would lead to a more competitive landscape of the auto industry in the long run that benefits consumers and leads to more efficient allocation of production.

[33]Consumers who switch away from an once-protected local product are much more likely to choose private products than imports for three main reasons. First, private products start with a larger market share than imports. Second, private products are much closer substitutes to the heavily protected SOE products as well as most JV products compared to the imports, as shown in Table 3. Third, consumers who change their minds due to a price discount are typically sensitive to prices and unlikely to purchase expensive imports. As can be seen from Figure 7, private firms stand to gain much more from the abolition of local protection compared to the foreign firms.

7 Conclusion

Based on the census of new passenger vehicle registrations from 2009 to 2011 in China, we provide robust evidence of local protectionism in China's automobile market using a regression discontinuity design. Through a structural model of vehicle demand and supply, we then quantify the impacts of local protectionism on market outcomes and show that abolishing local protection would significantly improve consumer welfare at the expense of a smaller loss of firm profits and tax revenues. In addition, the shift of production from high-cost SOEs to low-cost private firms would make resource allocations more efficient across firms and foster productivity growth. Our findings therefore call for close attention of central policy makers on eradicating trade barriers across regions and facilitating market integration within the country as China tries to spawn the next wave of economic growth.

While our study is the first to examine the impacts of local protectionism on market outcomes and social welfare focusing on an output market in China, future research could explore its long-term impacts on market structure such as firm entry and exit, innovation and productivity. This would help us understand the extent to which local protectionism has led to the salient features observed in this industry such as a large number of automakers, production capacity being scattered around the country, and low capacity utilization. In addition, it would be interesting to further explore the incentives of local governments and understand the balances they are trying to strike between consumer welfare, GDP growth, and tax revenue.

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Appendices

A home bias by Firm

The table below shows the market share in sales by firm at the national level and in the home market (where the firm is headquartered). The last column is the percentage difference in the share of dealers at the national level and in the home market. Most private firms do not fare much better in their home markets; every single SOE has very stark advantage in its home market; JVs lie somewhere in-between. The differences in dealer counts are typically below those in sales.

Table 1: home bias by Firm

Firm	National Share	Home Share	% Difference in Sales	% Difference in Dealers %
Private Firms				
BYD	4.70%	4.93%	5%	15%
Geely	3.73%	2.10%	-44%	-22%
Great Wall	2.04%	3.33%	63%	3%
Lifan	0.38%	0.99%	161%	91%
Zotye	0.30%	0.25%	-17%	-37%
SOEs				
Chery	4.70%	11.70%	149%	72%
FAW	2.41%	7.27%	202%	177%
Xiali	2.36%	16.40%	595%	341%
Chana	1.52%	4.60%	203%	181%
JAC	1.32%	5.49%	316%	139%
Haima	1.30%	2.67%	105%	77%
Brilliance	0.87%	3.07%	253%	222%
JVs				
VW Shanghai	9.98%	28.16%	182%	85%
GM Shanghai	9.98%	18.06%	81%	68%
VW FAW	7.90%	21.57%	173%	51%
Hyundai Beijing	6.55%	7.50%	14%	8%
Nissan Dongfeng	5.69%	11.43%	101%	41%
Toyota FAW	4.95%	4.30%	-13%	3%
Ford Changan	3.97%	6.82%	72%	70%
Honda Guangzhou	3.76%	7.11%	89%	79%
PSA Dongfeng	3.37%	11.27%	234%	78%
Kia Yueda	3.29%	3.31%	1%	21%
Honda Dongfeng	2.55%	4.90%	93%	27%
Toyota Guangzhou	2.48%	5.46%	120%	55%
Suzuki Changan	1.91%	2.25%	18%	-5%
GM Shanghai Wuling	0.83%	3.70%	343%	197%
Suzuki Changhe	0.82%	1.36%	66%	138%
BMW Brilliance	0.64%	0.57%	11%	23%

B Regional Variations in Dealer Discounts

Our analysis is based on MSRPs rather than retail prices and we do not have the comprehensive retail price data for the study period. If the discounts are heavier in the local markets than the other markets, this would lead to the pattern of home bias. The purpose of this section is to examine the pattern of promotions based on a comprehensive dataset on dealer promotions in China from the Auto Home website on March 30, 2016. Our dataset covers 7,458 trims under 847 vehicle models that are sold in 1,176 counties across all 31 provinces in China. We drop all electric vehicles[34], which only became available in China in 2014. The total number of observations (trim-store) is around 1.5 million. For each trim in each retail store, we calculate its discount rate based on its in-store retail price and MSRP. We document the following data patterns on the variations in discount rates across trims and regions.

First, discount rates are typically low, especially for domestic brands. Table 2 below shows that average discount rate is about 5%, and about 40% of trim-by-store observations have no discount. Discount rates are below 10% for 95% of trims under domestic brands, while about 5% of JV or imported brands have heavy discounts at 20% or above.

Table 2: Summary Statistics on Discount Rates

Firm type	No. of trims	% without discount	Mean	75th percentile	95th percentile	Max
Private	147,482	51.4%	2.4%	4.4%	9.1%	35.1%
JV	863,488	32.7%	6.9%	11.7%	18.8%	37.1%
SOE	246,589	49.3%	3.3%	5.7%	12.9%	35.1%
Imports	248,839	51.8%	4.9%	9.4%	19.0%	35.0%
All	1,510,846	40.4%	5.4%	9.9%	17.9%	63.3%

Second, there are some degree of regional variations in discount rates. Beijing has the highest mean discount rate at 7.6%, while Tibet has the lowest discount at 1.4%. Two thirds of provinces have mean discount rates between 4% and 6%. Overall, we observe heavier discounts in richer markets such as Beijing, Tianjin, and Shanghai. For each individual trim, there are also some variations in discount rates across regions and stores. Only 5.8% of trims have no discounts in all dealer stores , and only 2.5% have discounts in every store. On average, a trim has discounts in about 47% of stores where it is sold. Some trims have discounts in all but few stores, while others have discounts in only a few stores.

Finally, we find no evidence that dealer stores give heavier discounts to local product. Table 3 below shows results from a trim-level regression of discount rates on home-market dummies. The

[34] Some electric vehicles could have heavy discounts up to over 60% in some counties. These promotions are subsidies from government agencies in an effort to speed up the diffusion of this new technology. Subsidies of similar magnitude for electric vehicles are available in some areas in the U.S. as well (Li et al., 2016).

coefficients are small in magnitude, reflecting the low discount rates on average. After controlling for province and trim fixed effects, the discount rate for private automakers and SOEs are negative, implying that the discounts are even smaller in the local markets than in the other markets. Nevertheless, all three coefficients are small in magnitude and suggest no economically significant differences in discount rates between the local market and the other markets.

Table 3: Regional Variation in Promotions

	(1)		(2)		(3)	
	Est.	S.E.	Est.	S.E.	Est.	S.E.
HQ*Private	-3.39***	0.06	-0.18***	0.05	-0.41***	0.05
HQ*SOE	-2.31***	0.05	0.04	0.04	-0.16***	0.04
HQ*JV	1.66***	0.03	0.37***	0.02	-0.03	0.02
Trim FE	N		Y		Y	
Province FE	N		N		Y	

Note: The number of observations is 1,510,846. The dependent variable is the discount rate (in percentage points). * p<0.1, ** p<0.05, *** p<0.01.

C Logit Regressions

Our structural analysis incorporates local protection as price discounts for consumer purchase of local brands. Alternatively, we could capture local protection directly in the utility function as in the spatial discontinuity analysis in Section 3.2. In particular, we can specify the Berry-logit equation as the following:

$$
\begin{aligned}
ln(\frac{s_{jmt}}{s_{0mt}}) &= \beta_1 \mathrm{LCL}_{jm} + \beta_2 \mathrm{LCL}_{jm}\mathrm{SOE}_j + \beta_3 \mathrm{LCL}_{jm}\mathrm{JV}_j \\
&\quad -\alpha P_j + X_j\theta + \tau B_j + \delta_m + \eta_t + \xi_{jmt},
\end{aligned}
$$

where j denotes a product (vehicle model), m province, and t year. LCL is a dummy for local products. There are two types of local products based on if product j is produced by an automaker headquartered in market m or if it is produced by an automaker with a plant in market m. We allow these two types of local products to have different levels of home bias. P_j is the price of product j while X_j includes other observed vehicle attributes. B_j, δ_m, η_t are brand (e.g., Toyota), province, and year fixed effects, respectively. To deal with the price endogeneity due to unobserved vehicle attributes, we use the same set of IVs as discussed in section 4.3 in Columns (2) to (4).

We conduct regressions separately for individual and institution purchases at the provincial-year-product level as in our structural analysis. Table 4 below presents the results from Berry-logit regressions for individual purchases. We find that JV and especially SOEs have large and statistically significant home-market advantage in their headquarter provinces but private automakers do not. This is consistent with our results from the spatial discontinuity analysis in Section 3.2 and in-forms our choice of allowing two free parameters for local discount rates in our structural analysis. The coefficient for Plant*SOE is statistically significant in the IV specifications, suggesting that products from SOEs also enjoy an advantage in provinces where the automaker has manufacturing plants, although the magnitude is much smaller than the coefficient on HQ*SOE. The results also show that controlling for dealer network and product-market distance only erode a small part of home-market advantages for local JVs and SOEs, as suggested from the spatial discontinuity analysis. The results for institutional purchases presented in Table 5 show an even stronger home bias for JVs and SOEs as local governments often require and encourage the purchase of local products by government agencies and taxi companies for their vehicle fleet.

Table 4: Results from Berry-Logit Regressions, individual purchase

	OLS (1)	IV I (2)	IV II (3)	IV III (4)
HQ*Private	0.02	0.02	-0.10	0.04
	(0.11)	(0.18)	(0.16)	(0.15)
HQ*JV	0.65***	0.94***	0.81***	0.66***
	(0.06)	(0.06)	(0.07)	(0.06)
HQ*SOE	1.32***	1.59***	1.46***	1.32***
	(0.10)	(0.09)	(0.10)	(0.10)
Plant*Private	0.01	-0.05	0.02	0.02
	(0.09)	(0.12)	(0.13)	(0.13)
Plant*JV	-0.07	0.23***	0.20***	-0.07
	(0.07)	(0.06)	(0.06)	(0.06)
Plant*SOE	0.45**	0.29	0.33*	0.45***
	(0.22)	(0.19)	(0.19)	(0.18)
ln(Price)	-0.41***	-3.07***	-3.07***	-3.03***
	(0.06)	(0.18)	(0.18)	(0.18)
Distance	-0.06***		-0.06***	-0.05***
	(0.01)		(0.01)	(0.01)
No. of Dealers	0.01***			0.01***
	(0.00)			(0.00)

Notes: The number of observations is 19,505 with the unit of observation being province-year-product. All the regressions control for vehicle attributes, year and brand fixed effects, as well as market-specific preference for each vehicle type. p<0.1, ** p<0.05, *** p<0.01.

Table 5: Results from Berry-Logit Regressions, Institutional purchase

	OLS	IV I	IV II	IV III
	(1)	(2)	(3)	(4)
HQ*Private	0.02	0.02	-0.10	0.04
	(0.11)	(0.18)	(0.16)	(0.15)
HQ*JV	0.65***	0.94***	0.81***	0.66***
	(0.06)	(0.06)	(0.07)	(0.06)
HQ*SOE	1.32***	1.59***	1.46***	1.32***
	(0.10)	(0.09)	(0.10)	(0.10)
Plant*Private	0.01	-0.05	0.02	0.02
	(0.09)	(0.12)	(0.13)	(0.13)
Plant*JV	-0.07	0.23***	0.20***	-0.07
	(0.07)	(0.06)	(0.06)	(0.06)
Plant*SOE	0.45**	0.29	0.33*	0.45***
	(0.22)	(0.19)	(0.19)	(0.18)
ln(Price)	-0.41***	-3.07***	-3.07***	-3.03***
	(0.06)	(0.18)	(0.18)	(0.18)
Distance	-0.06***		-0.06***	-0.05***
	(0.01)		(0.01)	(0.01)
No. of Dealers	0.01***			0.01***
	(0.00)			(0.00)

Notes: The number of observations is 19,505 with the unit of observation being province-year-product. All the regressions control for vehicle attributes, year and brand fixed effects, as well as market-specific preference for each vehicle type. p<0.1, ** p<0.05, *** p<0.01.