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

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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. A salient feature of China's auto market is that vehicle models by joint ventures and state-owned enterprises command much higher market shares in their headquarter provinces than at the national level. Through county border analysis, falsification tests, and a consumer survey, we uncover protectionist policies such as subsidies to local brands as the primary contributing factor to the observed home bias. We then set up and estimate a market equilibrium model to quantify the impact of local protection, controlling for other demand and supply factors. Counterfactual analysis shows that local protection leads to significant consumer choice distortions and results in 21.9 billion yuan of consumer welfare loss, amounting to 41 percent of total subsidy. Provincial governments face a prisoner's dilemma: local protection reduces aggregate social welfare, but provincial governments have no incentive to unilaterally remove local protection. (*JEL* L24, L32, L62, O14, O18, P25, R12)

Preferential policies and practices that protect local firms against competition from nonlocal firms, which we refer to as local protectionism, are prevalent in developing countries where rent-seeking behaviors are common and federal oversight is weak. Young (2000) provides examples of discriminatory policies in China, such as local purchasing quotas, different product quality standards, and outright prohibition of nonlocal goods. Guriev, Yakovlev, and Zhuravskaya (2007) document instances in Russia where governments impose local content requirement on alcohol

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retailers or maintain sizable tariffs on products produced outside their jurisdiction. Local protectionism also appears in regulations in the developed countries. Klier and Linn (2013) show that regulatory policies such as the fuel tax and the emission standards implicitly discriminate products based on their countries of origin.[1] A 2004 report by the Canadian Chamber of Commerce documents interprovincial trade barriers in Canada that arise from different procurement standards among jurisdictions.

Local protectionism segregates the domestic economy, limits consumer choices, and distorts regional production away from patterns of comparative advantage (Young 2000, Donaldson 2015). Despite its prevalence and high social costs, local protectionism has not attracted adequate attention from most central governments. One possible explanation is that local protection takes various forms, many of which are implicit and hard to detect. In addition, the direct consequence of local protection—artificially high market shares of local products—rarely raises a red flag since it might be misconceived as a natural consequence of consumer preference or the advantages of local producers. As a result, there is little empirical analysis on the intensity of local protectionism and its welfare consequences. The goal of this paper is to fill this gap by leveraging detailed information from the census of new vehicle registration records in China. Our results show that local protection in China's auto industry is considerably stronger than what is suggested by scattered anecdotal evidence and has led to significant choice distortions and welfare losses.

Our point of departure is the striking empirical pattern in which 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 refer to as "home bias."[2] We examine several potential explanations for home bias such as transportation costs, access to dealers, consumer tastes, and consumer ethnocentrism. We first show that factors like transportation costs, access to dealers, and consumer demographics cannot explain away home bias, which persists in contiguous counties across province borders where these factors are similar. This analysis is implemented via a county-border design following the literature (Holmes 1998; Dube, Lester, and Reich 2010; Hagedorn, Manovskii, and Mitman 2016; Kroft et al. 2020). We then illustrate using falsification tests and a consumer survey that nonpolicy factors that change across province borders, such as local TV advertising, consumer tastes, and consumer ethnocentrism, are also inconsistent with the data patterns of home bias. For example, they do not explain the *absence* of home bias for private firms. We conclude that local protectionism is the main factor contributing to home bias in China's automobile industry.

[1] The United States has a more stringent tail pipe emission standard on nitrogen oxides than the European Union does. This puts diesel vehicles (mainly produced by the EU automakers) in a competitive disadvantage in the US market. In addition, the Corporate Average Fuel Economy standards in the United States are less stringent for light trucks (sport-utility vehicles (SUVs), pickup trucks, and vans) than passenger cars, implicitly favoring the Big Three US automakers.

[2] 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. The home bias we study is a province-of-origin effect within a country.

To quantify the impact of local protectionism on market competition and social welfare, we set up and estimate a market equilibrium model in the spirit of Berry, Levinsohn, and Pakes (1995; hereafter, BLP), incorporating local protectionism as a percentage discount for local products. Our model suggests that local protection is equivalent to a price discount of 18 percent for JV products and 31 percent for SOE products, which increases sales by JVs and SOEs in their headquarter provinces by 61 percent and 249 percent, respectively. These discounts are equivalent to 51 billion yuan in subsidy for local products, or US$8 billion during 2009–2011 at the 2011 exchange rate. Counterfactual analysis shows that choice distortions induced by local protection reduce consumer welfare by 12.6 billion yuan (US$2 billion). Upward price revisions by protected firms further increase consumer welfare loss to 21.9 billion yuan (US$3.4 billion). Consumer welfare loss is sizable (41 percent) relative to the magnitude of these discriminatory policies. Net social welfare loss is 8.4 billion yuan (US$1.3 billion) when we take into account the impact on firm profits and tax revenue.

It is worth noting that consumer welfare loss (in the absence of price adjustments) is entirely driven by choice distortions. Its magnitude is solely determined by the gap in intrinsic utilities between a consumer's top choice in the absence of local protection and the suboptimal subsidized product and is *independent* of the size of subsidy. In addition, the size of consumer welfare losses is independent of the exact form of local protection, be it monetary subsidies or favorable treatment of local cars.

In addition to the loss in social welfare, our analysis reveals several other downsides of local protection. First, we find that private firms are more cost efficient than JVs and SOEs by around 7 percent. Policies that benefit JVs and SOEs at the expense of private firms would harm long-run productive efficiency of the automobile industry. Second, local protection is highly regressive: 78 percent of its benefits go to the top 10 percent richest households. Finally, our results highlight a prisoner's dilemma among policymakers. Implementing local protection is the dominant strategy for most provincial governments, because local profits and tax gains loom larger than the consumer welfare loss. However, society as a whole is worse off because local protection hurts nonlocal firms and induces choice distortions. Therefore, eradicating these discriminatory policies requires effective oversight by the central government.

Our analysis has several limitations. We do not observe local protection—which is opaque and obscure—directly and estimate its magnitude using a demand analysis. Our model attributes all home bias that is not explained by vehicle attributes and consumer preferences to local protection. While we show that nonpolicy factors (transportation costs, consumer preferences, etc.) play a modest role in explaining home bias, to the extent that they matter, our estimate of local protection will include these nonpolicy measures that affect demand but are not adequately controlled in the empirical analysis. This would make our welfare loss estimate an upper bound. On the other hand, our analysis is static, abstracts away from dynamic consequences of local protection (inefficient production allocation and firm entry and exit), and ignores the welfare cost of collecting taxes to finance subsidies. Accounting for these additional distortions could triple the net welfare loss estimate reported above, as discussed in Section VD.

This study makes the following three contributions to the literature. First, it relates to the literature on home bias in international trade using disaggregate data (e.g., Head and Mayer 2015). Two papers are closely related to ours. Goldberg and Verboven (2001) study price dispersion in the European car market and document stronger consumer preference for national brands. Coşar et al. (2018) disentangle supply-driven sources from demand-driven ones and find consumer preference for home brands to be the single most important contributing factor of home bias. Our study contributes to this strand of literature by analyzing home bias in the context of domestic trade. We show that local governments' protective policy, instead of consumer preference, is the main driver of home bias in our context, where most households are first-time buyers and formation of consumer preference (e.g., brand loyalty) is in its early stage.[3] Our study is of particular policy relevance since it highlights an often overlooked source of home bias, whose negative welfare impacts could be mediated through appropriate policy changes and federal oversight.

Second, our study adds to an emerging literature on domestic trade frictions (Ramondo, Rodríguez-Clare, and Saborío-Rodríguez 2016). Recent studies focus on freight costs or costs that are associated with geographical barriers (Anderson, Milot, and Yotov 2014; Donaldson 2018; Coşar and Fajgelbaum 2016). We evaluate frictions that arise from protective policies and introduce a framework to quantify the welfare consequences of both observed and unobserved forms of local protection. To our best knowledge, this is the first study that quantifies local protection's welfare consequences as a result of choice distortions. Our paper also relates to the literature on local protectionism in China. Previous studies focus on detecting local protection by examining the deviation in the spatial pattern of production from comparative advantage using aggregate data (Young 2000, Bai et al. 2004, Poncet 2005, Holz 2009). Bai and Liu (2019) offer a related concurrent study that employs a difference-in-difference framework to examine the effect of trade barriers on firm export activities.

Finally, our paper contributes to the literature on resource misallocation (Hsieh and Klenow 2009; Brandt, Tombe, and Zhu 2009; Fajgelbaum et al. 2018). Different from the previous literature that studies the input market, our analysis examines market frictions induced by government policies in a product market. We show that such frictions change the relative prices of products based on their origin of production and result in inefficient production allocation. A better understanding of how interregional trade barriers (including local protectionism) affect market competition and social welfare has important implications for policies in both China and other economies facing such barriers.

The rest of the paper is organized as follows. Section I gives an overview of China's automobile industry and discusses our datasets. Section II presents descriptive evidence on home bias, examines different underlying reasons, and uncovers local protectionism as the main contributing factor. We then incorporate local protection into a market equilibrium model of vehicle demand and supply in Section III and present the estimation results in Section IV. Section V quantifies the welfare

[3] Understanding how these distortive policies shape consumer preference in the long run is an interesting topic, though it is beyond the scope of this analysis.

impact of local protectionism and discusses provincial governments' private incentives to protect local firms. Section VI concludes.

I. Background and Data

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

A. *Local Protectionism*

We define local protectionism as policies and practices that protect local firms against competition from nonlocal firms, which, strictly speaking, is illegal in China. The Anti-Unfair Competition Law that was passed in 1993 explicitly prohibits municipal or provincial governments from giving preferential treatment to local firms. In a 2009 blueprint to strengthen the national automobile industry, the central government called on local governments to report and abolish discriminatory policies and practices that favor local firms.[4]

Because of these regulations, protectionist policies in the automobile industry are often kept low profile and seldom documented. However, anecdotal evidence shows that local protection is prevalent and has morphed into many forms. We compile a list of over 100 examples from online searches with keywords like "subsidy + promote automobile industry." Many of them are tagged to industrial policies, such as subsidies for locally produced electric vehicles, or rebates to farmers who purchase locally produced minivans and pickup trucks. Others include direct subsidies and tax incentives for purchasing local passenger vehicles, procurement requirements for local government agencies and taxi companies, tail pipe emission standards that favor local brands, waivers of tolls, priority access to express lanes or exemptions from road usage restrictions, preferential treatment in issuing dealer permits, and sometimes taxes levied on nonlocal automobiles.[5,6]

Table 1 presents ten examples that involve direct monetary transfers to buyers of locally made cars. The seventh 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 (hereafter, "FAW") but not to the brands by FAW's JV

[4] Local protection is likely to violate the national treatment principle of the World Trade Organization, which prohibits discrimination via taxation and other regulations between imported and domestically produced goods.

[5] Yu et al. (2014), an article in the *Wall Street Journal* on May 23, 2014, reports that government subsidy to 22 publicly traded automakers in China amounted to 2.1 billion yuan in 2011 and increased to 4.6 billion in 2013. The article acknowledges that "(t)he subsidies come in many forms, including local government mandates and subsidies for purchases of locally made cars, making a total figure for local and national financial help difficult to calculate."

[6] A famous example of local protectionism is the "war of license fees" between Shanghai and Hubei province in the late 1990s. Starting from the early 1990s, the 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 the local automobile industry, the 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 nonlocal brands. In retaliation, Hubei province, the headquarter province of China's Second Automotive Group (also known as Dongfeng Auto), charged an extra fee of 70,000 yuan to Santana buyers "to establish a fund to help workers of companies going through hardship."

Table 1—Examples of Local Protectionism

Case	From	To	Location	Size	Eligibility
1	3/1/09	12/31/09	Hebei	10% or 5,000 yuan	Local minivans
2	7/1/09	12/31/09	Heilongjiang	15% or 7,500 yuan	Local minivans
3	8/18/09	Unknown	Henan	3% or 1,500 yuan	Local brands
4	3/07/11	Unknown	Guangxi	Lower purchase tax	Local brands
5	1/1/12	12/31/12	Chongqing	Total 300 mill. yuan	Changan Automotive
6	4/4/12	12/31/12	Anhui	3,000 yuan	Local brands for taxi
7	7/1/12	6/30/13	Changchun, Jilin	3,500–7,000 yuan	FAW indigenous brands
8	5/1/15	4/30/16	Fuzhou, Jiangxi	5%–10%	Jiangling Automotive
9	11/15/15	12/15/15	Guangxi	1,500–2,000 yuan	Local brands
10	12/21/15	Unknown	Harbin	Up to 60%	Local electric vehicles

Source: Official government documents from online searches

subsidiaries.[7] As a case study, online Appendix A evaluates this subsidy and documents a significant impact on sales of targeted FAW brands in Changchun, Jilin, relative to other cities in Jilin. The large sales increase is limited to targeted FAW brands. Other FAW brands, including brands by joint venture FAW-Volkswagen, exhibited no sales gains during the policy window, as one would expect.

Local protectionism in China arises from a combination of factors. First, market reforms started in 1978 made economic development the primary responsibility of local governments. GDP growth became the foremost measure of performance in the cadre evaluation system.[8] In addition, China's decentralized fiscal system under which expenditures are mostly financed by local revenue creates high incentives for government officials to seek a strong local economy (Jin, Qian, and Weingast 2005). There often exists a dynamic and reciprocal relationship between local governments and firms: governments favor connected firms through better access to credit and tax deductions, while firms return favors in providing assistance such as tax revenue to local governments (Lei 2016). Both the performance evaluation system and the fiscal decentralization have led to interjurisdictional competition and discriminatory policies that protect local firms against competition from nonlocal firms.

Second, government officials often derive private benefits from local JVs and SOEs. Governments appoint the top executives of JVs and SOEs in their jurisdiction, and there appears to be a revolving door between top executives in these companies and government officials. As a result, officials can directly benefit from local SOEs, ranging from finding jobs for their relatives in these companies to eliciting monetary support for public projects and even private usage.[9]

Third, the central government has not been effective in regulating interregional trades. The Commerce Clause in the US Constitution explicitly prohibits state regulations that interfere with or discriminate against interstate commerce. This to

[7] 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.

[8] Effective implementation of the one-child policy used to be another important criterion. In recent years, environmental measures are added to the evaluation system.

[9] 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.

a large extent frees the United States from the likes of the discriminatory policies observed in China, though some interstate trade barriers also persist in the United States (Fajgelbaum et al. 2018). In contrast, our empirical evidence suggests that enforcement in China has been ineffective despite similar laws since 1993.

The intensity of local protection can be different across firms. In general, SOEs are treated most favorably because of their importance to the local economy and close ties between their top executives and local government officials. Bai et al. (2004) find stronger local protectionism in industries where SOEs account for a larger output share. JVs lie between SOEs and private firms in the spectrum of preferential treatment. All JVs are owned in majority by the Chinese partners by law; in practice, these Chinese partners are always SOEs. Private firms are less likely to benefit from local protection since they typically have weak political connections.[10]

B. *The Chinese Automobile Industry*

China's automobile industry has grown from virtually nonexistent 30 years ago to the largest in the world. Online Appendix Figure F.1 shows annual sales of new passenger vehicles in the United States and China. The total number of new passenger vehicles sold in China increased from 0.85 million in 2001 to 21.1 million in 2015, surpassing the United States in 2009. The growth in China during this period accounted for 75 percent of the growth in the worldwide automobile industry.

All major international automakers have production capacity in China. Following the strategy of "exchange market for technology," or "quid pro quo" (Holmes, McGrattan, and Prescott 2015; Bai et al. 2020), the Chinese government requires foreign automakers to form joint ventures with domestic automakers in order to set up a production facility and limits foreign partners' ownership to less than 50 percent. During our sample period, joint ventures account for 68.7 percent of total sales. Private automakers, SOEs, and imports account for 11.4 percent, 16.7 percent, and 3.1 percent of total sales, respectively.

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 22 out of 31 provinces. During China's Eleventh Five-Year Plan from 2005 to 2010, all of these provinces designated the automobile industry as a strategic industry that enjoys 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 small compared to the United States. In 2015, there are over 60 automakers producing in China, and the top 6 dominant firms account for 46 percent of national sales. In contrast, in the United States, there are 15 automakers, and the top 6 firms control 77 percent of the market.

[10] According to private conversations with local officials, growth of private firms is discounted in officials' political achievement evaluation and often attributed to market economy reforms.

C. *Data*

Our analysis is based on four main datasets: (i) the universe of new vehicle registration records from 2009 to 2011, from the State Administration of Industry and Commerce, (ii) trim-level vehicle attributes from R. L. Polk and Company (henceforth, Polk; part of Information Handling Services Markit), (iii) city-level household demographics from the 2005 One-Percent Population Survey, and (iv) annual surveys of new vehicle buyers by Ford Motor Company. The fine spatial resolution of vehicle registration records allows us to examine home bias in small geographical areas. Vehicle attributes, the population survey, and the new-buyer survey provide additional information we need to estimate the market equilibrium model and quantify the welfare impact of local protectionism.

The vehicle registration data report the month and county of registration, the firm and model name of the vehicle registered, and major attributes such as transmission type, fuel type, and engine size as well as the car buyer's gender and birth year. We also observe whether the license is for an individual or institutional purchase.[11] We define a model by its name, transmission type, and fuel type, and we aggregate sales of each model to county and province, separately for individual and institutional purchases. Except when stated explicitly, our empirical analysis limits to automobiles sold for individual purchases and excludes institutional purchases, the latter of which are often government procurement and driven by nonmarket considerations.

Our raw dataset includes 683 distinct models. We keep the most popular models that together account for 95 percent of national sales in each year. Doing so has a couple of benefits. First, sales of small brands are likely measured with errors. Second, dropping small brands that are not marketed nationally avoids inflating the home bias estimate.[12] Our final sample has a total of 179, 218, and 234 models in 2009, 2010, and 2011, respectively, all of which are major national brands. For example, 25 out of 31 provinces report positive sales for all 234 models in 2011. These models are produced by 38 domestic firms (6 private firms, 20 JVs, and 12 SOEs) and 14 foreign firms. The total number of observations is 19,505 at the province-model-year level and 885,736 at the county-model-year level.[13] We retrieve headquarter location for each firm and plant location for each model from the firms' websites.

In addition to sales (registrations) data, we have compiled additional data on car attributes and consumer demographics. We first merge the sales data with vehicle characteristics from Polk, including the manufacturer suggested retail price (MSRP) (yuan), vehicle type (sedan, SUV, or multipurpose vehicle (MPV)), vehicle segment, vehicle size (square meters (m^2)), engine size (liters), horsepower (kilowatts), weight (tons), and fuel economy (liters per 100 kilometers (km)). All attributes are observed at the trim level, and we aggregate them to the model level

[11] Institutional purchases account for about 10 percent of all registration records. This is very different from Europe, where half of new vehicle registrations belong to company cars (Dimitropoulos et al. 2014).

[12] Many small brands have modest sales in the home market and single-digit sales in some nonlocal markets. Home bias of these brands is sensitive to measurement errors and tends to be artificially high.

[13] Unlike in the United States, city is a higher level of administrative unit than county in China. As of September 2011, there are 332 cities and 2,854 counties in China.

Table 2—Summary Statistics of Key Variables

Variable	Mean	Standard deviation	Min	Max
Sales	1,259	2,263	1	60,612
Real price (1,000 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	0	1
MPV	0.06	0.24	0	1
Number of dealers	19.2	21.5	0	137
Distance to headquarter (1,000 km)	1.5	1.1	0	5.2

Notes: The number of province-model-year observations is 19,505. Sales are annual units sold by model and province. The number of dealers is by province and brand.

using simple averages. MSRPs are set by manufacturers and are the same nationwide for each model year. Finally, we collect data on the dealer network by firm and city in March 2016, which provide useful information on spatial differences in consumers' access to car dealers. Discounts offered by individual dealers may lead to transaction prices that are different from the MSRPs. However, MSRP is likely a reasonable approximation of the unobserved transaction price for two reasons. First, according to store-level price information that we scraped from Autohome.com, heavy discounts are uncommon: 40 percent of trim-by-store observations have no discount, 25 percent have discounts below 10 percent, and only 3 percent have a 20 percent discount or above. More importantly, dealer stores do not give more discount to local products. Hence, using MSRP in place of the transaction price should not introduce bias in the estimates of local protection.[14]

MSRP in China includes value-added tax and consumption tax as well as import tariffs when applicable.[15] It does not include sales tax. Sales tax is usually 10 percent but was revised down to 5 percent and 7.5 percent for vehicles with engine displacement of no more than 1.6 liters in 2009 and 2010, respectively. We add sales tax to MSRP and deflate it to the 2011 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 car buyers in China. Finally, we multiply fuel economy by regional gasoline prices to construct fuel cost per 100 km for each model that varies by province and year.

Table 2 reports the summary statistics. The average price of a vehicle is 184,700 yuan (US$28,000). The average price is similar to that observed in the US market, but the price range is larger in China. Table 3 shows the product portfolio for

[14] Online Appendix B provides more details on the price data. Autohome.com is a major, privately run gateway website that regularly updates information on car features and industry headlines. Note that "minimum retail price maintenance (RPM)," whereby automakers prohibit dealers from selling below a preset price, was common in China in our sample period. For example, the China Automobile Dealers Association complained in 2011 that large automakers imposed RPM and exclusive territory to reduce price competition among dealers.

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

Table 3—Mean Values of Key Variables by Firm Type

Variable	Private	JV	SOE	Imports
Sales	1,289	1,478	1,057	382
Real price (1,000 yuan)	81.0	189.7	102.2	428.1
Fuel cost (yuan/100 km)	45.9	49.6	48.2	61.7
Engine size (liter)	1.6	1.8	1.6	2.5
Vehicle size (m^2)	7.2	7.8	7.4	8.3
Auto transmission	0.06	0.55	0.22	1
SUV	0.21	0.12	0.09	0.56
MPV	0	0.04	0.13	0.11
Number of dealers	13.5	24.6	10.0	12.0
Observations	2,168	11,444	3,888	2,005

Notes: Sales are annual units sold by model and province. The number of dealers is by province by brand.

different firms. JV brands have higher prices, bigger vehicle sizes, and more powerful engines compared to private or SOE brands. In addition, JVs have a more extensive dealer network, and a larger fraction of their products have automatic transmission. JV products are twice as expensive as their domestic counterparts. The price gap is likely driven by higher unobserved qualities and better brand recognition, which we capture using brand fixed effects in our estimation. Imported products are typically luxury brands, and the majority of them are SUVs.

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 percent population survey in 2005, separately for urban and rural households. Such comprehensive data at the individual level for recent years are difficult to find. Consequently, for each year in our sample period, we scale the provincial income distribution from the 2005 survey to match the provincial average reported in the annual China Statistical Yearbooks. This implicitly assumes 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 distribution for new vehicle buyers from an annual survey conducted by Ford Motor.[16] The survey breaks annual household income into four brackets: less than 48,000 yuan, 48,000–96,000 yuan, 96,000–144,000 yuan, and greater than or equal to 144,000 yuan, and it 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 5 segments: mini/small sedan, compact sedan, medium/large sedan, SUV, and MPV.

The first panel of online Appendix Table F.1 compares the income distribution among all vehicle buyers to that of the general population. The second panel of online Appendix Table F.1 reports consumers' income distribution for each of the

[16] The survey covers 20,500, 23,900, and 34,000 vehicle buyers in 2009, 2010, and 2011, respectively.

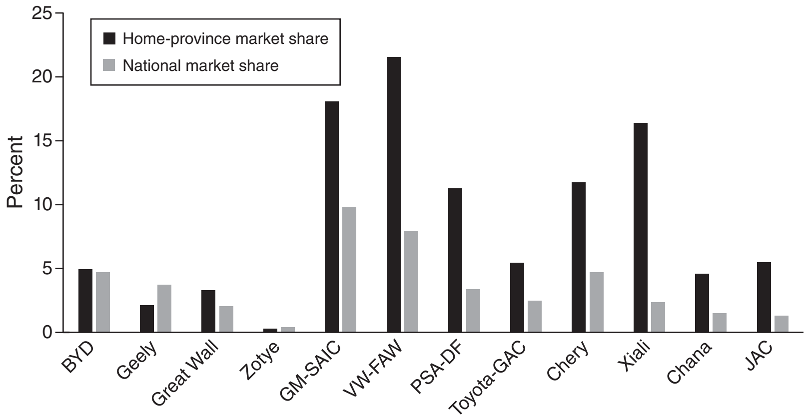

Figure 1. Home-Province and National Market Shares

Notes: Market shares are calculated using sales volume over the three-year sample period. The first four firms are private, followed by four JVs and four SOEs, respectively. Online Appendix C.1 documents the patterns for all 38 firms in our sample.

five vehicle segments in 2011. High-income households are disproportionately more likely to buy new vehicles, especially high-end sedans and SUVs. In 2011, only 4 percent of Chinese households have an annual income above 144,000 (the median car price in our sample), yet they account for 47 percent of the sales of medium/large sedans and SUVs and 36 percent of MPVs. Income information for the general population and new vehicle buyers helps us to identify price elasticity and income elasticity, as discussed in detail in Section IIIC.

II. Home Bias and Its Contributing Factors

As local protectionism takes a myriad of forms and is often opaque and unreported, we cannot systematically document all the relevant policies and directly estimate their impact. Instead, we analyze patterns of home bias in China's automobile industry, examine potential contributing factors, and isolate the role of government protection as the leading cause.

A. *Home Bias in China's Automobile Industry*

We begin by comparing automakers' national market share with their market share in the home province. Figure 1 displays these numbers for 12 large automakers (4 private firms followed by 4 JVs and 4 SOEs, respectively).[17] One striking pattern is the contrast between private and nonprivate firms: while there is no noticeable difference for private firms, JVs and SOEs command much higher market shares in their home provinces than they do at the national level. One notable

[17] For each of the three firm types, we select firms that have the largest national market shares. These 12 firms together account for 54.9 percent of total vehicle sales in China between 2009 and 2011.

example is Xiali: it accounts for only 2.4 percent of national new vehicle sales but captures 16.4 percent of sales in its home province Tianjin. Table C.1 in online Appendix C.1 documents the patterns of home bias for all 38 automakers in our sample, where home bias is defined as the ratio between the home-province market share and national market share minus 1. The median home bias is 87 percent for JVs, 236 percent for SOEs, and −8 percent for domestic firms. We run a *t*-test on the null hypothesis that the monthly home-province market share and national market share are equal, and we reject the null at the 1 percent significance level for all SOEs and all but 3 JVs.[18]

Institutional automobile purchases exhibit an even stronger home bias for JVs and SOEs: the median home bias is 152 percent for JVs, 479 percent for SOEs, and 15 percent for private firms (Table C.1 in online Appendix C.1). Large home bias in institutional purchases is evidence of government favoritism, because these procurement decisions are often under the discretion of local officials. In addition, variation in home bias for institutional purchases is a strong predictor for home bias in individual purchases (Figure C.1 in online Appendix C.2). In comparison, other factors such as firm age, market dominance, and price are largely uncorrelated with home bias observed in private purchases.

These patterns hint at favorable government policies as a potential driving force of home bias. However, there could be other important sources, including transportation costs, access to auto dealers, local advertising, consumer taste, and consumer ethnocentrism. In the rest of Section II, we use a county-border regression design, falsification tests, and a consumer survey to examine each of these nonpolicy factors in turn.

B. *Home Bias in Clusters of Adjacent Counties*

We first examine the extent of home bias using a subsample of counties that straddle a common province border. Specifically, we group adjacent counties on different sides of province borders into clusters of two to four counties and drop clusters with counties in Tibet, Xinjiang, and Qinghai.[19] Our county-cluster sample consists of 630 counties in 285 clusters, as shown in different patterns in Figure 2. In each cluster, at least one county is located in a province that has a local automaker.[20]

This "county-border" design, similar in spirit to studies such as Holmes (1998); Dube, Lester, and Reich (2010); Hagedorn, Manovskii, and Mitman (2016); Kroft et al. (2020); and others in the literature, exploits the fact that protective policies change sharply across province borders but many nonpolicy factors stay similar, such as transportation costs, speed of delivery, and access to dealer stores.[21] Residents in adjacent counties also share similar demographics and tastes, as

[18] The *p*-values for the three JVs are BMW Brilliance (0.09), Suzuki Chana (0.16), and Kia Yueda (0.66).

[19] Counties in these three provinces are sparsely populated and very different from the rest of the country.

[20] Most clusters are composed of two counties that share the longest borders. We also allow larger clusters when three or four counties share a significant portion of the borders. There are 229 clusters with 2 counties, 52 clusters with 3 counties, and 4 clusters with 4 counties.

[21] Subsidies or rebates are usually tied to the city of residence. In addition, residents outside the home province cannot enjoy benefits such as waivers of fees and tolls that are effective locally.

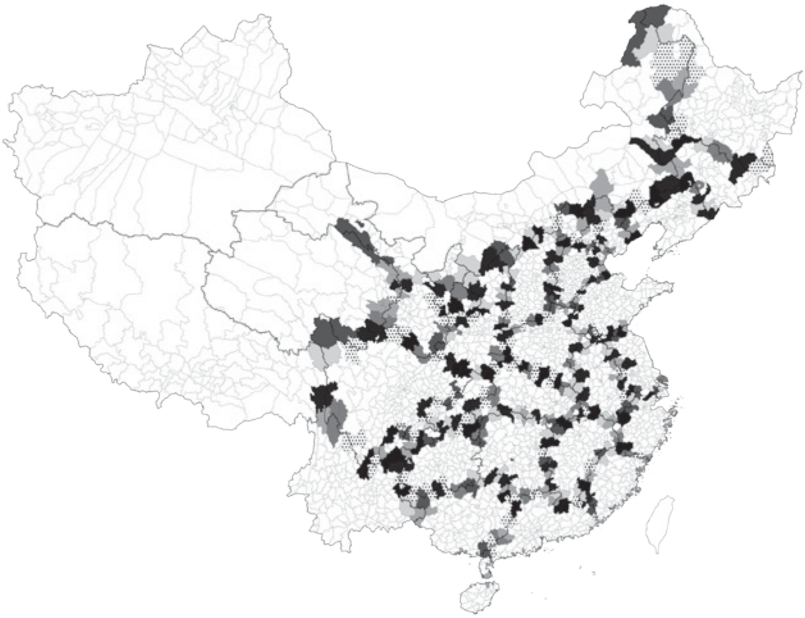

Figure 2. Clusters of Counties along Province Borders

Notes: 630 counties on province borders are grouped into 285 clusters. Adjacent clusters are in different patterns to help distinguish them. There are 229 clusters with 2 counties, 52 clusters with 3 counties, and 4 clusters with 4 counties. Clusters along the borders between Tibet, Xinjiang, and Qinghai are dropped. Other counties that are on provincial borders but not shaded are missing from our car sales data.

Table 4—Differences in Consumer Demographics between Counties

	Full sample		County clusters		County clusters, GDP ratio $<$ 1.6	
	Mean	SD	Mean	SD	Mean	SD
	(1)		(2)		(3)	
Ratio in GDP per capita	2.92	2.63	2.07	1.41	1.29	0.24
Ratio in mean urban household income	1.31	0.29	1.24	0.21	1.25	0.22
Ratio in mean rural household income	1.73	0.78	1.45	0.47	1.29	0.27
Difference in mean age	0.67	1.02	0.45	0.43	0.42	0.37
Difference in percentage male	3.51	3.66	2.50	2.71	2.37	2.45

Notes: All variables are as of year 2009. Column 1 uses the full sample of all counties. Column 2 uses counties in the county clusters. Column 3 further restricts to clusters where the ratio between the highest and lowest county-level GDP per capita is capped at 1.6. In each column, we randomly draw 500 pairs of counties (for columns 2 and 3, the pair is from the same cluster), compute the ratio (or difference) between the larger and smaller value for each statistic, and report the mean and standard deviation of the ratios (or differences). Data on GDP per capita and urban and rural household income come from the China Statistical Yearbooks. Mean age and gender ratio are calculated using information on individual car buyers from our vehicle registration records.

confirmed in Table 4, which compares two randomly drawn counties for three different samples: (i) the full sample of all counties in the country, (ii) counties in the clusters mentioned above, and (iii) counties in clusters where the GDP per capita ratio between the highest and the lowest counties is capped at 1.6. Households in the third sample are much more homogeneous than two random counties in the country and present similar socioeconomic attributes.

We implement the county-border design by the following regression framework to quantify the extent of home bias:

$$\ln(sales_{jmt}) = \beta_1 HQ_{jm} PRI_j + \beta_2 HQ_{jm} JV_j + \beta_3 HQ_{jm} SOE_j + \gamma_1 PL_{jm} PRI_j + \gamma_2 PL_{jm} JV_j + \gamma_3 PL_{jm} SOE_j + \phi_{jc} + \lambda_j + \lambda_m + \lambda_t + \varepsilon_{jmt}, \tag{1}$$

where the dependent variable $\ln(sales_{jmt})$ is the sales in log for model j in county m (located in cluster c) at year t. The indicator HQ_{jm} takes value 1 for all counties in the headquarter province of model j. Further, PRI_j, JV_j, and SOE_j are dummies for models of private firms, joint ventures, and state-owned enterprises. In addition to headquarters, we also allow for a "production location" bias for models that are produced outside their headquarter provinces. The dummy PL_{jm} takes value 1 for all counties in the province that produces model j but is not the firm's headquarter province. The terms λ_j, λ_m, and λ_t are model, county, and year fixed effects, respectively.

Importantly, we allow for a cluster-specific taste dummy for each model ϕ_{jc}, where cluster c contains county m. This controls for demand shocks and preference heterogeneity for different models at the cluster level. For example, SUVs are popular in hilly areas, and luxury brands are in high demand in wealthy places. With cluster-model interactions, we are essentially using variations in the market share of a specific model among adjacent counties within each cluster to quantify the extent of home bias.

Table 5 summarizes the results. Column 1 uses the full sample, while column 2 limits to counties in the clusters (on provincial borders). The standard errors for these two columns are clustered at the province level. Consistent with the evidence presented in Section IIA, in both columns, JVs and SOEs exhibit a substantial home bias in their headquarter province. In contrast, there is no evidence that models produced by private firms have higher sales shares in their home market than in the national market. We also observe a sizable production-location premium for models by SOEs that benefit from a significant boost in sales in provinces that host their production plants.[22]

Column 3 uses the cluster sample as in column 2 and controls for cluster-model interactions ϕ_{jc}, corresponding to equation (1). The home bias parameters are estimated using differences in market shares across adjacent border counties. Standard errors are two-way clustered by province and by cluster. While the (modest) fall of point estimates on JV-headquarter and SOE-headquarter suggests that nonpolicy factors like transportation costs could play some role, the differences between estimates in columns 2 and 3 are not statistically significant at the 10 percent level.[23]

[22] A potential contributing factor is job benefits such as discounts for employees who buy cars from their own firms. It is not a significant source of home bias in our border-county sample, because only a handful of these counties have production facilities.

[23] We estimate columns 2 and 3 jointly using seemingly unrelated regression and test the null hypothesis that coefficients on HQ × Private, HQ × JV, and HQ × SOE are equal across the two specifications. The p-values are 0.26, 0.19, and 0.63, respectively.

Table 5—Home Bias by Firm Type

Dependent variable: log(sales)	Full sample (1)	County clusters (2)	County clusters (3)	County clusters GDP ratio < 1.6 (4)	County clusters GDP ratio < 1.6 (5)
HQ × Private	−0.16	−0.00	0.21	0.09	0.10
	(0.26)	(0.19)	(0.09)	(0.10)	(0.09)
HQ × JV	0.68	0.61	0.42	0.40	0.38
	(0.14)	(0.16)	(0.05)	(0.06)	(0.06)
HQ × SOE	1.09	1.03	0.95	0.87	0.81
	(0.13)	(0.15)	(0.05)	(0.07)	(0.07)
Plant × Private	0.14	−0.00	−0.02	−0.08	−0.07
	(0.17)	(0.11)	(0.11)	(0.19)	(0.19)
Plant × JV	0.15	0.18	0.03	−0.10	−0.10
	(0.10)	(0.10)	(0.07)	(0.10)	(0.10)
Plant × SOE	0.63	0.61	0.42	0.67	0.68
	(0.06)	(0.06)	(0.11)	(0.16)	(0.16)
Number of dealers					0.02
					(0.01)
Observations	885,189	180,398	180,398	77,309	77,309
R^2	0.56	0.55	0.76	0.74	0.74
Model FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
Cluster-model FE			✓	✓	✓

Notes: All regressions are estimated using OLS. Standard errors are clustered by province for column 1 and 2 and two-way clustered by province and by cluster for columns 3 to 5. Column 1 uses the full sample of counties. Columns 2 and 3 use counties in the border-county sample. Column 4 and 5 restrict to clusters within which the ratio between the highest and lowest GDP per capita across counties is less than 1.6. Column 5 controls for the number of dealers. Plant takes value 1 in counties in the province that hosts the assembly plant of the model but is not the headquarter province.

The economically and statistically significant estimates from the county-border design and the similarity in magnitude across columns indicate that transportation costs that are similar across bordering counties are not the main source of home bias. There is a small home bias for private firms in column 3. A close inspection reveals that this is largely driven by Great Wall, which produces cheap cars in Hebei province that shares borders with wealthy municipalities Beijing and Tianjin. In column 4, we further restrict the sample to more homogeneous clusters where the ratio between the highest and lowest GDP per capital across counties is capped at 1.6. We find no home bias for private firms but similar home biases for JVs and SOEs.

One might be concerned that consumers in adjacent counties may not have equal access to the dealer network, since not all dealers have a license to sell to residents from other provinces. In column 5, we add the number of dealers in the city of each border county as a control. The dealer network is important: one additional store increases sales by about 2 percent. The magnitude of home bias for JVs and SOEs, as well as the plant premium for SOEs, remains similar to other columns.

The main takeaway from the county-border design is that factors that are similar across province borders, such as transportation costs, access to dealers, and consumer demographics, play a modest role in driving home biases for JV and SOE products. Still, home bias that persists in clusters of border counties could be driven by nonpolicy factors that change across province borders. Three plausible causes are consumer tastes, consumer ethnocentrism, and local TV advertising. We examine them in the next section.

C. *Other Explanations for Home Bias*

Consumer Tastes for Product Attributes.—While residents in adjacent counties are more similar, Table 4 shows that there are still some differences in consumer demographics. These differences, together with unobserved factors such as local traditions or customs, could result in different tastes for cars across provincial borders. Home bias could arise if firms design product attributes that cater to the needs and tastes of local consumers.

Were home bias driven by a better match between consumer tastes and attributes of local products, we should expect higher sales for nonlocal products that have similar attributes as the local products. This motivates a falsification test in which we replace each local model with its closest nonlocal counterparts ("clones"). We divide all models in our sample to 242 groups of twins or triplets that have nearly identical attributes but different and nonadjacent headquarter provinces. Models in each group are made by firms of the same ownership type, have the same transmission, and fall in the same vehicle segment. In addition, we match them on price, fuel economy, engine size, and vehicle size.[24] For example, Dongfeng-Honda Civic (based in Hubei) is matched with FAW-Toyota Corolla (based in Tianjin).

We switch headquarters and plant locations between models in each of the 242 groups; for example, Dongfeng-Honda Civic is assigned to Tianjin while FAW-Toyota Corolla is assigned to Hubei, and replicate the analysis as in Section IIB. Results are reported in Table 6. Across all columns, we find no evidence of "home bias" or "production plant premium" for these clones with a fake-headquarter status or local production status: the coefficients are either insignificant or have the wrong sign. We conclude that home bias for JVs and SOEs is not driven by a better match between consumer tastes and attributes of local products.

Consumer Ethnocentrism.—Consumer ethnocentrism, or an innate preference for local products, is another potential source of home bias. Consumers at different sides of provincial borders see themselves as citizens of different provinces. Some people might trust local products more or consider buying local cars as a way to signal their identity or to support local enterprises. Consumer ethnocentrism, however, is at odds with two empirical patterns. First, home bias is uncorrelated with the firm age or national market share of a model (Figure C.3 to C.5 in online Appendix C.2 for details), while one would expect stronger consumer ethnocentrism for older firms and better-performing models. Second, there is no home bias for private firms. It is difficult to imagine any reason why innate preference is large for SOEs but entirely absent for private firms, given that SOEs and private firms have similar characteristics and produce similar products.

[24] Matching by attributes is sometimes subjective. Nonetheless, the choices are obvious in most cases, as competing products in the same segment have similar attributes. The median price range in a group is 5,000 yuan ($800).

Table 6—Falsification Test with Placebo Headquarters and Plants

Dependent variable: log(sales)	Full sample (1)	County clusters (2)	County clusters (3)	County clusters, GDP ratio < 1.6 (4)	County clusters, GDP ratio < 1.6 (5)
Fake HQ × Private	−0.19	−0.10	0.08	−0.01	−0.01
	(0.21)	(0.23)	(0.10)	(0.11)	(0.10)
Fake HQ × JV	−0.04	−0.05	−0.03	−0.01	−0.00
	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)
Fake HQ × SOE	−0.26	−0.31	−0.04	−0.09	−0.09
	(0.09)	(0.11)	(0.06)	(0.09)	(0.09)
Fake Plant × Private	0.13	0.06	0.07	0.14	0.14
	(0.10)	(0.11)	(0.08)	(0.09)	(0.09)
Fake Plant × JV	−0.05	−0.01	−0.09	−0.07	−0.07
	(0.10)	(0.13)	(0.05)	(0.05)	(0.05)
Fake Plant × SOE	−0.07	−0.15	0.03	−0.08	−0.08
	(0.08)	(0.07)	(0.25)	(0.14)	(0.14)
Number of dealers					0.03
					(0.00)
Observations	885,189	180,398	180,398	77,309	77,309
R^2	0.55	0.54	0.75	0.73	0.74
Model FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓
Cluster-model FE			✓	✓	✓

Notes: All regressions are estimated using OLS. Same specification as in Table 5, except the headquarter province and plant province are swapped between similar models within each group.

Even if SOEs are systematically more "pride-worthy" than private firms for some unobserved reasons, consumers should at least know which firms are local and which are SOEs.[25] To directly gauge consumers' awareness of the local status and firm ownership, we conducted a survey in November 2016 in Chongqing, a large municipality in Southwest China. Residents in this city are more likely than residents in other provinces to recognize local firms, as the city is much smaller in its geographical scope compared to a province. We ran the survey at dealer stores, where visitors were requested to fill out a simple questionnaire. The questionnaire covers two local firms, LiFan (a local private firm) and Chana (a local SOE), in addition to three major nonlocal auto firms. We asked the respondents to choose the local status and ownership type for each of the five firms and rate the importance of "buying local" in their purchase decisions. Online Appendix D contains details of the survey questionnaire and results.

Our survey shows that people have limited knowledge about their local brands. Only one out of the 297 respondents correctly answered all questions on local and ownership status. Thirty-one percent of them (92) correctly recognized that Lifan and Chana were local firms and that LiFan was private while Chana was a SOE, though many (28) mistakenly chose at least 1 nonlocal firm as local. Among these 92 respondents who knew the local firms, "buying local" is the least important factor

[25] JVs are easy to identify because their firm names contain the names of both the domestic partner and the foreign firm.

in their purchase decisions, compared with prices, engine displacement, fuel economy, and brand reputation.

TV Advertising.—Advertising on local TV channels whose coverage aligns with provincial borders could potentially create discontinuity in vehicle demand at the border. However, survey evidence suggests that this is unlikely to be important. First, a survey by China's National Information Center in 2012 shows that TV advertising is the tenth (out of 16) most frequently cited source of information for car purchases. Only 12 percent of the survey correspondents considered it to have any influence in their purchase decisions, and only 2.1 percent cited it as the most important source of information. In addition, local TV channels account for less than 20 percent of national viewership in 2010. Finally, Chinese automakers spend a small fraction of revenue on advertising, less than 1 percent in 2014 (Nielsen-CCData 2015). While we do not observe advertising expenditure by firm and region, it is unclear why JVs and SOEs advertise heavily in their home province but private firms do not.

Comparison with the US Market.—Our last piece of evidence comes from the automobile market in the United States, whose Commerce Clause in its Constitution explicitly prohibits state regulations that interfere with interstate commerce. We prefer the United States to other countries because it possesses several similarities to China: both are large countries, and both have strong local governments. The United States has 50 states. China has 31 provinces. Total passenger vehicle sales were similar between China and the US in 2009. The main difference is that the auto industry in the United States has over 100 years of history, while China's passenger car industry was nascent at the turn of the century. Most Chinese households are first-time buyers during our data period, and the formation of consumer preference (e.g., brand loyalty) is in its early stage. Brand preference is likely much stronger in the United States than it is in China.

We collect the vehicle sales data from the United States at the state-quarter level over the same period of 2009 to 2011. The home market of a firm is the set of states where the firm has an assembly plant, since most auto firms have headquarters outside the United States. Panel A of online Appendix Figure F.2 compares home-state market shares and national market shares for all 16 automakers that have assembly plants in the United States. We find home bias for five firms (Chrysler, Ford, General Motors (GM), Kia, and Nissan) in the range between 30 percent and 65 percent. This is substantially smaller than home bias in China, which is 87 percent for JVs and 236 percent for SOEs. Home bias diminishes considerably when we use neighboring states as a comparison group, as shown in panel B.[26] Evidence from the United States suggests that in the absence of government favoritism, factors such as consumer tastes are unlikely to give rise to the large home biases that we observe in China's automobile industry.

[26] We have looked closely at the Big Three since they are headquartered in the United States and offer the closest comparison to SOEs in China. The Big Three have a home bias of 60 percent in their headquarter state Michigan compared to adjacent states. This is not surprising given their dominant presence in Michigan for over a century and their importance for the local economy and employment. Still, the magnitude of home bias is a quarter of the median home bias for SOEs in our sample.

To summarize, we document significant home bias in car purchases for JVs and SOEs, but not for private automakers. Home bias persists in adjacent counties across provincial borders, which suggests that transportation costs, access to dealers, and consumer demographics—factors that do not change across provincial borders—play at most a modest role. In addition, the falsification tests and a consumer survey rule out consumer tastes and consumer ethnocentrism as an explanation. Finally, home bias in the United States, a country with less government intervention of the interstate commerce, is much more modest. These findings point to local protectionism as the primary driver of home bias observed in our setting.

Next, we build a structural model to estimate the impact of local protectionism on consumer choices, market structure, and social welfare.

III. A Structural Model of the Automobile Market

In this section, we first present a model of consumer demand for new vehicles, taking into consideration both observed and unobserved consumer heterogeneity. We incorporate local protection as a price discount for protected firms in their headquarter province. Then we model firms' pricing decisions as equilibrium responses from a Bertrand-Nash competition. We conclude the section with brief discussions on identification and estimation strategies.

A. *Demand*

We define a province-year as a market. In each market, households choose from J_{mt} models to maximize their utility. The indirect utility of household i buying product j in market m and year t is a function of product attributes and household demographics:

$$u_{ijmt} = \bar{u}\Big(\big(1 - \rho_{jm}\big)\, p_{jt}^{0}, X_{jt}, \xi_{jmt}, D_{imt}\Big) + \varepsilon_{ijmt},$$

where the first component $\bar{u}((1 - \rho_{jm})\, p_{jt}^{0}, X_{jt}, \xi_{jmt}, D_{imt})$ is defined below and ε_{ijmt} is a random taste shock that follows the type-I extreme value distribution. Utility from the outside option is normalized to ε_{i0mt}.

Since local protectionism is opaque and takes many forms, it is impractical to formally incorporate all forms of protection into our model. Instead, we model these protective policies as price discounts for local brands. Let p_{jt}^{0} denote the retail price of product j in year t, which is the same nationwide (as discussed in Section IC). Effective price is

$$p_{jmt} = \big(1 - \rho_{jm}\big)\, p_{jt}^{0}, \tag{2}$$

where ρ_{jm} stands for the discount rate for product j in market m. In our baseline model, ρ_{jm} takes the value of ρ_1, ρ_2, or ρ_3 if j is a local private product, a local JV product, or a local SOE product, respectively, and 0 otherwise. One should interpret those parameters as capturing the impact of all forms of protective policies on utility.

We specify utility $\bar{u}(p_{jmt}, X_{jt}, \xi_{jmt}, D_{imt})$ as the following, where D_{imt} stands for household attributes:

$$(3) \qquad \bar{u}_{ijmt} = -\alpha_{imt} p_{jmt} + \sum_{k=1}^{K} X_{jkt} \tilde{\beta}_{ikmt} + \xi_{jmt} + B_j + \zeta_{jm} + \eta_t.$$

Household i's marginal utility from a dollar, α_{imt}, is defined as

$$\alpha_{imt} = e^{\bar{\alpha}_{imt} + \alpha_1 \ln(y_{imt}) + \sigma_p \nu_{imt}}.$$

The first term $e^{\bar{\alpha}_{imt}}$ denotes the base level of price sensitivity. It takes four different values, one for each of the four income brackets in the new-vehicle-buyer survey. The second component $\alpha_1 \ln(y_{imt})$ captures how disutility from price changes continuously with household income. One would expect α_1 to be negative since wealthy households are less price sensitive. While, in principle, the log-income coefficient α_1 is identified, in practice it is difficult to estimate and often delivers extreme elasticities for households with low or high income levels. We follow Berry, Levinsohn, and Pakes (1999) and set α_1 to -1. The third term $\sigma_p \nu_{imt}$ is a random shock that captures idiosyncratic factors that influence price elasticity, such as inheritance and assets accumulated in the past. Note that ν_{imt} is assumed to follow the standard normal distribution and σ_p is the dispersion parameter to be estimated. Both y_{imt} and p_{imt} are in million yuan.

The term X_{jt} is a vector of observed product attributes, including a constant term, log of fuel cost, vehicle size, engine size, a dummy for automatic transmission. We also control for the distance between the destination market and the headquarter province as well as the number of dealers in each province-brand pair.

We define household i's taste for attribute k as

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

which follows a normal distribution with mean $\bar{\beta}_k$ and standard deviation σ_k. Different households may have different tastes due to unobserved demographics or idiosyncratic preference. We allow random tastes (nondegenerate σ_k) for the constant term and fuel cost in addition to price, and we shut down dispersions for all other attributes ($\sigma_k = 0$).[27] The random taste for the constant term reflects heterogeneity in households' outside option, such as cars currently owned and public transportation.

The third element, ξ_{jmt}, captures all unobserved product attributes, such as advertising and quality of customer service as perceived by buyers in market m and year t. The remaining terms in equation (3) are B_j, ζ_{jm}, and η_t, which stand for brand, province by vehicle segment, and year fixed effects, respectively.[28] We include interactions between province and vehicle segment, ζ_{jm}, to control for market-specific

[27] Random coefficients for engine size and vehicle size are rarely significant when included.

[28] To avoid introducing additional notations and with some abuse of notations, we use B_j to denote brand fixed effects and ζ_{jm} to denote province by vehicle segment fixed effect.

preference for different vehicle types. For example, provinces with a larger average household size or hilly terrains are likely to exhibit stronger preference for SUVs.

To facilitate the discussion on identification and estimation below, we rewrite the utility function as $u_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt}$, where

$$\delta_{jmt} = X_{jt}\bar{\beta} + \xi_{jmt} + B_j + \zeta_{jm} + \eta_t, \tag{4}$$

$$\mu_{ijmt} = -e^{\bar{\alpha}_{imt} + \alpha_1 \ln(y_{imt}) + \sigma_p \nu_{imt}} \times p_{jmt} + \sum_{k=1}^{K} X_{jkt}\sigma_k \nu_{ikmt}. \tag{5}$$

The household-specific utility, μ_{ijmt}, depends on household characteristics, while δ_{jmt}, the mean utility, does not.

We use θ_1 to denote parameters in δ_{jmt}, which we refer to as linear parameters, and θ_2 to denote parameters in μ_{ijmt}, which we refer to as nonlinear parameters, following Berry, Levinsohn, and Pakes (1995). The nonlinear parameters include $\theta_2 = \{\bar{\alpha}_1, \bar{\alpha}_2, \bar{\alpha}_3, \bar{\alpha}_4, \rho_1, \rho_2, \rho_3, \sigma_p, \sigma_1, \sigma_2\}$, where $\bar{\alpha}_1, \bar{\alpha}_2, \bar{\alpha}_3, \bar{\alpha}_4$ are price coefficients; ρ_1, ρ_2, ρ_3 are local protection discounts; and $\sigma_p, \sigma_1, \sigma_2$ measure the dispersion in random tastes for price, the outside option, and fuel cost, respectively. The probability that household i chooses product j is

$$\Pr_{ijmt}(p, X, \xi, y_{imt}, D_{imt}; \theta_1, \theta_2) = \frac{e^{\delta_{jmt}(\theta_1) + \mu_{ijmt}(\theta_2)}}{1 + \sum_{h=1}^{J_m}\left[e^{\delta_{hmt}(\theta_1) + \mu_{ihmt}(\theta_2)}\right]}. \tag{6}$$

We aggregate individual choice probabilities to obtain market shares and match them to our data.

Caveats: Our modeling choice has a few caveats. Note that demand is estimated at the province-year level. Ideally, we would like to incorporate the county border design into the structural demand model and estimate local protection using variations between adjacent counties. Unfortunately, this raises significant data and computational challenges. We do not observe county-level income distributions or micro moments on the fraction of new buyers in each income bracket for the county-border sample. In addition, since the county-border sample has a lower income relative to other counties, we cannot use this sample alone for our supply-side analysis where we examine firms' optimal pricing decisions (for which we need to estimate auto demand for all counties). Finally, estimating the nonlinear demand model at the county level is computationally prohibitive. As a result, we estimate demand at the province level and control for nonpolicy sources of home bias as best as we can. For example, we use the distance between destination market and headquarter province to control for transportation costs, the number of dealer stores to control for access to dealers, and market-specific income distribution to control for heterogeneous tastes driven by consumer demographics.

Second, in principle, our discount parameters capture effects of local protection as well as nonpolicy sources of home bias. We showed in Section IIA that factors other than protective policies play a modest role. If nonpolicy sources of home bias, such as consumer ethnocentrism and tastes for local products, do not differ systematically by firm ownership-type, then ρ_1, the home premium for private firms, would measure home bias driven by nonpolicy factors. The difference between ρ_2 (ρ_3) and ρ_1 reflects the effect of local protection for JVs (SOEs).

Third, we model local protection as a percentage subsidy, while, in reality, protection takes both monetary and nonmonetary forms. This simplification does not affect our estimate for consumer welfare loss from local protection, which depends on the extent of choice distortion and is *independent* of the form of protection. Whether local protection is monetary (direct subsidies) or implemented through nonmonetary discriminatory policies (restrictions in setting up dealers) does matter when we think about aggregate welfare costs to society. We discuss these issue in more details in Section V.

B. *Supply*

We estimate demand and supply separately. Our supply-side specification follows BLP with a few minor modifications. First, instead of choosing one price for each market, firms pick one price across all markets for each model in a year. National pricing is a reasonable approximation for the Chinese car market, because RPM is a common practice (Li, Xiao, and Liu 2015). Second, we explicitly model taxes as part of the profit function. Taxes levied on automobile purchases in China are high and can account for up to 50 percent of the final transaction price. This creates a significant wedge between the transaction price and the revenue that accrues to firms.

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

$$\begin{aligned}\pi_f &= \sum_{m=1}^{M}\sum_{j\in\mathcal{F}}\left(p_j^0 - T_j\left(p_j^0\right) - mc_j\right)M_m s_{jm}\\ &= \sum_{j\in\mathcal{F}}\left(p_j^0 - T_j\left(p_j^0\right) - mc_j\right)S_j,\end{aligned}$$

where $\mathcal{F}$ is the set of all products by firm f, p_j^0 is the MSRP, T_j refers to total tax and is a function of the sales price, and mc_j stands for marginal cost. Market size M_m is measured by the number of households in market m. The fraction of households that buy product j in market m is denoted as s_{jm}, while S_j represents product j's total quantity sold over all markets. Each firm chooses $\{p_j^0, j \in \mathcal{F}\}$ to maximize its total profit. Given this assumption, p_j^0 satisfies the following first-order condition:

$$S_j\left(1 - \frac{\partial T_j}{\partial p_j^0}\right) + \sum_{r\in\mathcal{F}}\left(p_r^0 - T_r - mc_r\right)\frac{\partial S_r}{\partial p_j^0} = 0, \quad \forall j.$$

Let Δ be a J-by-J matrix whose (j,r)th term is $-\left(\partial S_r/\partial p_j^0\right)$ if r and j are produced by the same firm and 0 otherwise. The first-order conditions can be written in vector notation as

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

which implies

$$p^0 = mc + T + \Delta^{-1}\left[S\left(1 - \frac{\partial T}{\partial p^0}\right)\right]. \tag{7}$$

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

In China, sales of new vehicles are subjected to 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.[29] Let p_j^0 denote the retail price paid by consumers and p_j^f denote manufacturer price (per-unit payment received by firm f). The relationships among retail price, manufacturer price, and taxes are

$$p_j^0 = \frac{p_j^f}{1 - t_j^c} \times \left(1 + t_j^{va} + t_j^s + t_j^{im}\right), \tag{8}$$

$$T_j = p_j^0 - p_j^f, \qquad \text{and} \qquad \frac{\partial T_j}{\partial p_j^0} = 1 - \frac{1 - t_j^c}{1 + t_j^{va} + t_j^s + t_j^{im}}.$$

We calculate T and $\partial T/\partial p^0$ using equation (8), derive Δ from demand estimates, and back out marginal cost for each model and year mc_{jt}. Marginal cost is assumed to be log-log in attributes

$$\ln(mc)_{jt} = W_{jt}\phi + \omega_{jt}, \tag{9}$$

where W_{jt} includes logs of vehicle attributes, firm-type dummies, and year dummies and ω_{jt} stands for unobserved cost shock to model j in year t. We are most interested in the coefficients of firm-type dummies, which capture relative cost efficiency between different types of firms.

C. *Identification and Estimation*

Our discussion on identification focuses on two sets of key parameters: (i) the coefficients that measure consumer price sensitivity $e^{\bar{\alpha}_{imt} - \ln(y_{imt}) + \sigma_p \nu_{imt}}$, which includes five parameters: $\{e^{\bar{\alpha}_1}, e^{\bar{\alpha}_2}, e^{\bar{\alpha}_3}, e^{\bar{\alpha}_4}, \sigma_p\}$, and (ii) price discounts that capture the extent of local protectionism: ρ_1, ρ_2, and ρ_3.

We use three sets of instruments to address both the endogeneity of price arising from its correlation with unobserved product attributes ξ_{jmt} and the fact that market shares need to be "instrumented" in a nonlinear model like ours (Berry and Haile 2014, Gandhi and Houde 2019). The first set of instruments, or the BLP instruments, includes the number of products in the same vehicle segment by the same firm and

[29] An unconventional feature of China's tax system is that the "pretax" price includes the consumption tax, which depends on the engine size of the vehicle. For example, if the pretax price is 100,000 yuan and the consumption tax is 25 percent, the manufacturer gets 75,000 yuan while the government collects 25,000 yuan as the consumption tax. The other three types of taxes are charged as a percentage of the pretax price. Valued-added tax is 17 percent for all models and import tariff is 25 percent for imported products, while sales tax is normally set at 10 percent but was lowered to 5 percent and 7.5 percent for vehicles with engine displacement of no more than 1.6 liters in 2009 and 2010, respectively.

the number of products in the same vehicle segment by rival firms. They capture the intensity of competition that affects firms' pricing decisions. Nonprice attributes are assumed to be orthogonal to ξ_{jmt} and serve as instruments for themselves.

The second set of instruments is consumption tax rate. The range of the vehicle consumption tax rates is large, from 1 percent for engine size equal to or smaller than 1.0 L to 40 percent for engine size above 4.0 L. The rationale for such a tax scheme is to promote sales of small and fuel-efficient vehicles to reduce pollution and congestion. Consumption tax rate is a strong instrument since it introduces discrete jumps in prices at different engine-size thresholds.

The third set of instruments exploits panel variations in household income. Online Appendix Table F.1 documents a noticeable increase in income level over our sample period: the fraction of households with annual income less than 48,000 yuan dropped from 69 percent in 2009 to 55 percent in 2011. Regional variation is also pronounced. In 2009, the median household income in the richest province is 54,000 yuan, which is around 3 times of that in the median province and over 5 times of that in the poorest province. We first construct differences in vehicle attributes following Gandhi and Houde (2019) and then interact these attribute differences with different quantiles of the income distribution in each market.

Besides these instruments, several data patterns help identify our key coefficients. First is the extent to which more expensive models have higher market shares in provinces with a higher household income. The second and more powerful source of identification comes from the Ford survey, which shows the fractions of households in each of the four income brackets among all new-car buyers and among buyers in each vehicle segment. Higher $\bar{\alpha}_i$ makes all consumers in income group i less likely to buy expensive cars, while larger σ_p increases the odds of rich households buying cheap cars and of poor households buying expensive ones. These micro moments help pin down $\bar{\alpha}_i$ for each income group and σ_p.

To identify the discount parameters, we add home-market dummies by ownership type to the list of instruments. By doing this, we require the unobserved product quality ξ_{jmt} to be orthogonal to the home-market status and thereby ensure that all home bias is captured by the discount parameters (once we control for observed attributes). Note that price sensitivity $\{e^{\bar{\alpha}_1}, e^{\bar{\alpha}_2}, e^{\bar{\alpha}_3}, e^{\bar{\alpha}_4}, \sigma_p\}$ and discount parameters $\{\rho_1, \rho_2, \rho_3\}$ are interdependent: more elastic demand means that smaller discounts suffice in matching the home bias observed in the data.

We estimate the demand model using simulated GMM with both macro- and micro-moment conditions. Macro moments are constructed by interacting excluded instruments discussed above with unobserved product quality ξ_{jmt}. Micro moments match the model-predicted fractions of buyers by income brackets and vehicle segments to the observed fractions in the Ford survey. There are 32 excluded macro moments and 45 micro moments for 10 nonlinear parameters.[30]

[30] For micro moments, we have 3 years, 4 income brackets, and 5 segments as well as all segments combined, which leads to $3 \times 5 \times 3 = 45$ micro moments (we lose one degree of freedom since within each year and segment, the shares of the 4 income brackets add up to 1). There are 32 excluded IVs, which are the number of own and rival products in the same segment; consumption tax rate and the total tax rate; urban income quantiles; sum of differences in attributes with other products in the same segment; dummies for local private, JV, and SOE products; and their interactions. Our demand model also include 175 exogenous regressors: 7 product attributes, 92

Table 7—Results from the Random Coefficient Model

	Est.	SE	Est.	SE
	(1)		(2)	
Linear parameters				
log(Fuel cost)	−4.53	0.23	−1.37	0.21
log(Displacement)	1.85	0.17	3.30	0.16
log(Size)	5.21	0.24	6.64	0.22
Auto transmission	0.39	0.03	0.64	0.03
Distance to headquarter	−0.05	0.02	−0.06	0.02
Number of dealers	0.01	0.00	0.01	0.00
Price and discount parameters				
$e^{\bar{\alpha}_1}$	10.23	4.40	27.99	2.88
$e^{\bar{\alpha}_2}$	1.46	0.18	17.03	1.29
$e^{\bar{\alpha}_3}$	0.68	0.18	6.27	0.39
$e^{\bar{\alpha}_4}$	0.50	0.23	5.39	0.42
Private discount, ρ_1	0.04	0.07	0.04	0.04
JV discount, ρ_2	0.22	0.04	0.18	0.02
SOE discount, ρ_3	0.36	0.05	0.31	0.03
Dispersion parameters				
Constant, σ_1	4.29	2.63	3.32	0.20
log(Fuel cost), σ_2	3.16	0.73	0.95	0.05
Price, σ_p	0.24	0.10	1.26	0.04

Notes: Column 1 uses only the macro moments. Column 2 uses both the macro and micro moments. The number of observations is 19,505. First-stage *F*-statistic is 741.5 for both columns.

Our macro moments are based on 19,505 observations in our estimation sample. The number of observations that underlie our micro moments is the number of survey respondents, which increases from 20,500 in 2009 to 34,000 in 2011. We scale each set of the micro moments by the appropriate number of observations and implement the estimation using simulated optimal GMM with a nested contraction mapping, as is now standard in the BLP literature. In the first stage, we use weighting matrix $\begin{pmatrix} (Z'Z)^{-1} & 0 \\ 0 & \Omega^{-1} \end{pmatrix}$, where Z is the set of excluded instruments and Ω is the variance-covariance matrix of the micro moments, to obtain consistent estimates of the parameters and the optimal weighting matrix. In the second stage, we reestimate the model with the optimal weighting matrix to obtain the final parameter estimates. Online Appendix E provides more details on how we address computational issues in estimating our model.

IV. Estimation Results

A. *Demand*

Table 7 shows estimation results from our baseline demand model. Column 1 uses the macro moments only, and column 2 uses both macro and micro moments.

province-by-vehicle-type dummies, 2 year fixed effects, 1 dummy for Beijing 2011 lottery policy that reduces car demand, and 73 brand dummies.

We present coefficients on key vehicle attributes, price and discount parameters, and three parameters that measure the dispersion in random coefficients.

The set of estimates without micro moments (column 1) ascribes most car sales to the second-lowest income bracket and fails to predict the income shares reported in the Ford survey. In addition, this model underestimates consumer price sensitivity and overestimates the discount parameters. We focus on results from column 2 in subsequent discussions.

Coefficients on all key vehicle attributes are intuitively signed and statistically significant. All else equal, consumers prefer more fuel-efficient and more powerful and larger vehicles as well as vehicles with automatic transmission. A 10 percent increase in fuel cost reduces sales by around 12.2 percent, while a 10 percent increase in displacement and vehicle size increases sales by around 37.0 percent and 88.3 percent, respectively. Conversion from manual to automatic transmission would increase sales by around 89.7 percent. In addition, sales increase with the number of local dealers and decrease with distance to the headquarter province.

The price coefficient $\bar{\alpha}$ falls monotonically as we move up the income brackets, which implies that sensitivity to prices falls more than proportionally as income increases. Consider a car priced at 140,000 yuan, the median price in our sample in 2011. Demand elasticities (shutting down ν^p_{imt}) are -163.3, -33.1, -7.3, and -2.6 when income is 24,000, 72,000, 120,000, and 288,000 yuan, respectively.[31] Since most low-income households have little accumulated wealth and limited access to bank loans, they rarely purchase new vehicles. On the other hand, $\hat{\sigma}_p = 1.37$ implies that there is a large dispersion in price sensitivity at a given income level. Consider two consumers with the same income ($y_{1mt} = y_{2mt} =$ 120,000 yuan) but different draws of the random price sensitivity ($\nu^p_{1mt} = 1$, and $\nu^p_{2mt} = -1$). Our model predicts that for a car priced at 140,000 yuan, demand elasticity is -25.7 and -2.1 for those two households, respectively. Note that σ_p captures unobserved wealth and other factors that relate to the propensity of buying cars and helps explain demand for expensive vehicles in provinces that have few high-income households.

Our preferred estimates with micro moments in column 2 is able to match the Ford survey well (Table 8). The largest prediction error across income brackets is 3.2 percent, and the average prediction error is only 1.5 percent. The fit for the segment-specific income shares is also good.

We plot own-price elasticities against vehicle prices for our data sample in 2011 in online Appendix Figure F.3. Own-price elasticities range from -2.43 to -4.08, with a median of -3.39. The median price elasticity for private, JV, SOE, and imported products is -3.61, -3.30, -3.62 and -2.82, respectively. In general, more expensive models have less elastic demand since they target more wealthy households. The magnitudes of the own-price elasticities are similar to those obtained from the US market (Berry, Levinsohn, and Pakes 1995; Petrin 2002). Although average household income is much lower in China than in the United States, our micro moments suggest that most prospective car buyers in China come from a relatively affluent

[31] Income is in millions of yuan in our estimation, so $y_{imt} = 0.024, 0.072, 0.12, 0.288$ for this example.

Table 8—Model Fit in Micro Moments

Year	Income group	Observed share	Predicted share specification (1)	Predicted share specification (2)
2009	<48k	15.8%	7.7%	16.2%
	48k–96k	33.6%	64.0%	31.8%
	96k–144k	32.0%	18.1%	30.2%
	>144k	18.6%	10.2%	21.8%
2010	<48k	10.9%	4.7%	11.2%
	48k–96k	26.9%	64.5%	29.0%
	96k–144k	33.3%	19.9%	31.4%
	>144k	28.9%	10.9%	28.4%
2011	<48k	9.3%	5.7%	10.2%
	48k–96k	26.2%	61.5%	27.7%
	96k–144k	33.7%	19.1%	34.4%
	>144k	30.8%	13.7%	27.7%

Notes: Specifications (1) and (2) correspond to columns 1 and 2 of Table 7, respectively. We do not use observed shares as moments in specification (1) but target them in specification (2).

class that have less elastic demand. The aggregate market elasticity is -1.07: total sales would fall by 1.07 percent if prices for all cars increase by 1 percent.

The discount for local private products, ρ_1, is estimated to be close to 0 and statistically insignificant. This is consistent with the evidence in Section IIA that private firms have no appreciable home bias. Hence, we interpret $\hat{\rho}_2$ and $\hat{\rho}_3$ as the impact of local protection, which is equivalent to an 18 percent discount in retail price for local JV products and 31 percent discount for local SOE products. These estimates appear reasonable for several reasons. First, Table 1 shows that reported subsidies for local vehicles can be as high as 15 percent of the retail price. Our estimates encapsulate other forms of local protection, such as waivers of registration fees and tolls and access to express lanes. Second, these estimates are broadly consistent with estimates from our county-border design. For example, an 18 percent price discount raises JV products' local market share by 61 percent, which is similar to the 52 percent boost in market share implied by estimates in column 5 of Table 5. Lastly, for Chongqing in 2012, where we were able to uncover the total reported subsidy (Table 1), our estimated subsidy of 472 million yuan according to our structural demand analysis is comparable to the reported subsidy of 300 million. Our estimate is somewhat higher since it also captures nonmonetary forms of local protection.

To examine the robustness of our results, we estimate a few alternative specifications of the demand model and summarize the results in online Appendix Table F.2. Column 1 excludes both distance and the number of dealers from the list of controls, and column 2 excludes the number of dealers. In column 3, we allow discounts rates to differ over time. In column 4, we divide provinces with local JVs and local SOEs into two tiers, each based on the extent of home bias in institutional procurement, and estimate tier-specific discount rates.[32] Reassuringly, estimates of the linear

[32] We divide the 14 provinces that have local JVs into 2 tiers of 7 provinces each and divide the 10 provinces that have local SOEs into 2 tiers of 6 and 4 provinces each. We put 6 provinces into the lower tier since there is a big discrete jump in home bias in institutional procurement between the sixth and seventh province.

Table 9—Results from Cost-Side Estimations

	Est.	SE	Est.	SE	Est.	SE	Est.	SE
	(1)		(2)		(3)		(4)	
Ownership types								
Private	−0.11	0.03	−0.07	0.02	−0.07	0.02	−0.07	0.02
JV	0.22	0.02	0.00	0.02	0.00	0.02		
JV (Europe)							0.05	0.02
JV (Japan)							−0.03	0.02
JV (Korea)							0.01	0.02
JV (United States)							−0.01	0.02
Imports	0.34	0.04	0.11	0.03	0.11	0.03	0.11	0.03
Attributes								
log(Fuel cost)	−0.03	0.13	0.33	0.09	0.33	0.09	0.27	0.09
log(Displacement)	1.25	0.10	0.81	0.07	0.81	0.07	0.87	0.07
log(Size)	0.82	0.13	0.94	0.09	0.94	0.09	0.89	0.09
Auto trans.	0.19	0.02	0.13	0.02	0.13	0.01	0.14	0.01
SUV	0.00	0.03	0.07	0.02	0.07	0.02	0.08	0.02
MPV	−0.10	0.04	−0.09	0.03	−0.09	0.02	−0.08	0.02
Fixed effects								
Year FE	Y		Y		Y		Y	
Brand FE estimates	N		Y		Y		Y	
$\bar{\xi}$	N		N		Y		Y	

Notes: The number of observations is 631. The reference ownership type is SOE. We import brand fixed effect estimates and $\bar{\xi}$ from the demand estimation.

parameters, price coefficients, and dispersion parameters in all four columns are similar to those under the baseline specification. Column 4 reports larger discount rates in provinces where we observe larger home bias in institutional procurement of cars. This result formalizes the descriptive evidence in Section IIA that home bias is greater in provinces where there exists a high level of government favoritism.

B. *Supply*

With the demand-side parameters, we use firms' pricing equation (7) to back out marginal costs for each model in each year. To examine how vehicle attributes and ownership type affect marginal costs, we regress log of marginal costs on these controls using equation (9) and report the results in Table 9. Column 1 includes logs of key vehicle attributes and separate dummies for automatic transmission, SUV, and MPV. Column 2 adds brand fixed effect estimates from Section IVA and their quadratic terms.[33] Column 3 further includes estimated $\hat{\xi}_{jmt}$ from the demand-side to control for unobserved product quality. We average $\hat{\xi}_{jmt}$ across provinces to obtain the national average. Column 4 breaks down JV products by the origin of the foreign partner.

The coefficients on car attributes are in general intuitive. Marginal costs are higher for larger engine size, larger cars, cars with automatic transmission, and SUVs. Multipurpose vehicles include a variety of specialized cars, including minibuses

[33] We cannot use brand dummies directly, since they absorb all of the ownership coefficients.

that are often of lower quality and cheaper. Their marginal cost is lower than sedans and SUVs.

We use SOEs as the reference group when we examine relative efficiency among four different ownership types. In column 1, the marginal cost of private firms is 11 percent lower than that of SOEs, while JVs and foreign firms have cost disadvantages as high as 22 percent and 34 percent. Such results are mostly driven by the different product mix between private/SOE and JV/foreign firms. Compared with domestic firms, JVs and foreign firms produce high-end products that are more likely to use high-quality inputs (leather seats, sunroof, more safety features, etc.). Once we control for brand-fixed-effect estimates (column 2 onward), the gaps in marginal costs shrink by a large margin. Private firms are still the most efficient among the four groups, and their marginal cost is about 7 percent lower than that of the SOEs. Imports have a 11 percent cost disadvantage that could be driven by high transportation costs.

Surprisingly, JVs do not seem to be more efficient than SOEs, even though all the foreign partners are well-known leading auto producers in the world. When we separate JVs by the country origin of their foreign partners, JVs with US and Japanese partners appear to be slightly more cost efficient than JVs with European or Korean partners, but the differences are mostly statistically insignificant. The fact that JVs do not appear more efficient than SOEs might be related to how they are managed. The domestic partner of every JV in our sample is an SOE.[34] These domestic partners hold at least a 50 percent stake in the JVs and in most cases control the operation and management of the firm, while the foreign partner mainly provides the technology.

The medium marginal cost of a private brand in our sample is around 41,800 yuan. Transferring vehicle production from private firms to JVs or SOEs would lead to a cost increase of about 7 percent, or around 3,000 yuan per vehicle.

V. Counterfactual Analysis

To quantify the impact of local protection on market outcomes and social welfare, we reset discount rates for local JV and SOE products to zero and simulate market outcomes when trade barriers across regions are eliminated. We do the exercise twice, first without any price change and second allowing auto firms to adjust prices in response to the removal of local protection. We then compare market outcomes and social welfare between the observed and simulated scenarios. We assume in our counterfactual exercises that removing local protection does not affect firms' choices of vehicle characteristics or the introduction and elimination of car models.[35]

[34] 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 partnership between a prominent private auto producer and a foreign producer happened in 2010, when Build Your Dreams (BYD) and Mercedes-Benz formed the joint venture BYD Daimler. Their first production debuted in 2014.

[35] Although local protection has large effects on home-market sales for JVs and SOEs, home-market sales are usually a small fraction of total sales since there are 31 provinces in China. As discussed in Section IIC, firms do not cater to local tastes in designing their products. Inducing firm or product entry could be an objective of local protection, but modeling these decisions is beyond the scope of this paper.

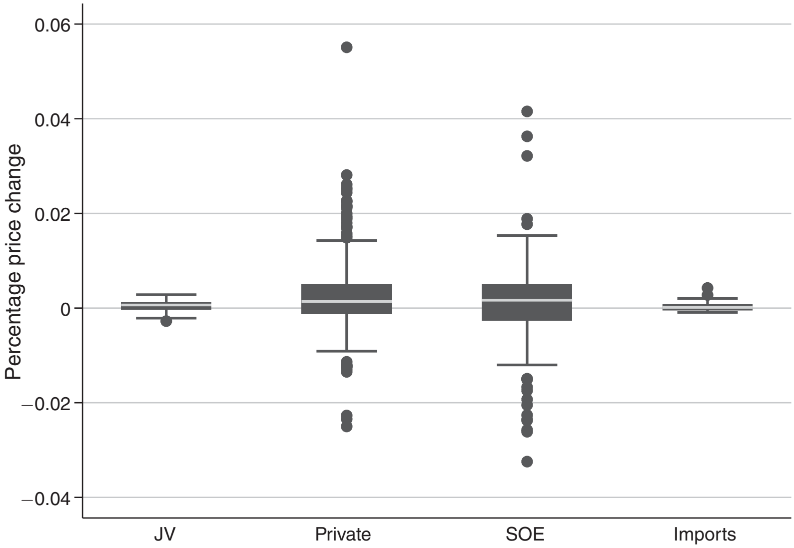

Figure 3. Percentage Price Changes by Firm Type

Notes: Each observation is a model-year. We start from a scenario without local protection and show the distribution of price changes for each firm type when we introduce local protection.

A. *Impacts on Market Outcomes*

To evaluate the impact of local protection on prices, we solve new equilibrium prices without local protection using equation (7) and plot the distributions of percentage price changes induced by local protection in Figure 3. Note that with multiproduct firms that experience demand shocks in one market but cannot price discriminate across different markets, patterns of price adjustments in our settings are more complex than that of a single-product firm in a single market.

Local protection enhances protected firms' market power locally. Not surprisingly, 64 percent of JV products and 66 percent of SOE products experience price increases as a result of greater market power in their home markets. The sign and magnitude of the price adjustments are highly correlated with the importance of the home market. For example, the largest price hike among SOE products (4.15 percent) is by Xiali Vela in 2009, whose home-market sales account for 72.8 percent of its total sales. Firms based in large and wealthy provinces tend to increase prices, while firms with small home markets tend to reduce prices to cope with stiffer competition in their nonlocal markets.

Price adjustments for private and imported products are smaller in absolute value. On one hand, competition from protected JV and SOE products exerts downward pressure on prices. On the other hand, prices are strategic substitutes. When JVs and SOEs increase their prices, this exerts upward pressure on prices of private and imported cars. The two effects offset each other, and net price adjustments are small.

Turning to quantity responses, we show in the top panel of Table 10 that local protection increases home-market sales of JVs and SOEs by 62.9 percent and 249.5 percent, respectively, when we fix prices at the observed level. Its impact on a firm's

Table 10—Impacts of Local Protection on Sales

Firm type	Home-market sales ('000)			National sales ('000)		
	Without protection	With protection	Percent change	Without protection	With protection	Percent change
Without price adjustment						
Private	217	208	−4.2%	2,862	2,794	−2.4%
JV	747	1,217	62.9%	16,652	16,877	1.3%
SOE	93	324	249.5%	3,957	4,111	3.9%
Imports				775	766	−1.1%
With price adjustment						
Private	216	208	−3.9%	2,849	2,794	−1.9%
JV	753	1,217	61.4%	16,706	16,877	1.0%
SOE	95	324	240.9%	3,980	4,111	3.3%
Imports				772	766	−0.9%

Notes: We observe sales with protection and simulate sales without local protection (with and without price adjustments). Sales are aggregated over the three-year sample period.

national sales is much less extreme. There are 31 provinces in China; home-market sales on average only account for 5 percent of a firm's total sales. In addition, when all provinces protect their local products, a JV or SOE benefits in its home province but faces stiffer competition elsewhere. Business stealing in other provinces counteracts gains in the home market. As a result, local protection increases the national sales of JVs and SOEs by only 1.3 percent and 3.9 percent, respectively.

National sales by private and foreign firms fall by 2.4 percent and 1.1 percent, respectively, as their prospective consumers switch to the protected local JV or SOE products. Local protection hurts the private firms more than foreign firms for two reasons. First, as shown in Table 3, products by private firms are closer substitutes to SOE products. Second, imported cars are typically bought by wealthy consumers who care less about price discounts.

Price adjustments—higher prices by JVs and SOEs in response to local protection—offset a small fraction of sales gains by JVs and SOEs. As shown in the bottom panel of Table 10, when we allow for price changes, local protection increases national sales of JVs and SOEs by 1.0 percent and 3.3 percent, respectively, and reduces those of private firms and foreign firms by 1.9 percent and 0.9 percent, respectively.

Next, we turn to substitution patterns induced by local protection, which are summarized in Table 11. We highlight three findings. First, consumers are much more likely to substitute between similar choices, which is intuitive. The top panel of Table 11 shows that in the absence of price adjustment, 64 percent of sales gains by local JV products as a result of local protection come from similar nonlocal products, while 36 percent come from the outside option. Similarly, 79 percent of households who would otherwise choose some JV product in the absence of local protection substitute to a local JV product. Second, although we find much stronger protection for local SOEs, JVs gain more sales in absolute terms because of their larger market shares. Lastly, local protection leads to 703,000 suboptimal vehicle choices between 2009 and 2011 when prices are held fixed. Allowing price

Table 11—Substitution Patterns Induced by Local Protection

	Substitute to ('000)				
Old choice	Private	JV	SOE	Imports	Do not buy
Without price updates					
Private		41	28		
JV		203	53		
SOE		54	25		
Import		8.2	0.4		
Do not buy		175	126		
With price updates					
Private	0.5	46	31	0.0	2.5
JV	13	284	77	4.2	50
SOE	10	72	37	0.1	28
Import	0.0	8.7	0.5	0.1	0.3
Do not buy	1.3	188	133	0.1	

Notes: We first simulate a scenario without local protection. We then start from the "without-protection" scenario, and simulate how choices of individual consumers change when we introduce local protection. Substitutions are aggregated over the three-year sample period.

adjustment increases the number of distortions to 986,000, or 4 percent of total vehicle sales over our sample period.

B. *Welfare Analysis*

We first evaluate the welfare consequences of local protection on consumer surplus. Local protection reduces consumer welfare through two channels. First, it leads to a modest increase in the average vehicle price, as shown in Figure 3. Second, and more importantly, local protection distorts consumer choices toward suboptimal JV or SOE products.

To illustrate the welfare impact 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 A and a surplus of 6,000 yuan from a local product B. Suppose the government in market m provides a subsidy of 5,000 yuan to each consumer who purchases B. The subsidy induces consumer i to choose B over A. This substitution results in a welfare loss of 4,000 yuan: the government spends 5,000 yuan subsidizing consumer i's vehicle purchase, but only increases her surplus by 1,000 yuan. Welfare loss occurs whenever local protection causes a consumer to choose a local brand that is different from her intrinsic top choice. Importantly, when a choice distortion occurs, the magnitude of the consumer welfare loss is solely determined by the gap in intrinsic utilities between a consumer's top choice in the absence of local protection and the suboptimal subsidized product, and it is *independent* of the size of subsidy. Here, consumer i's intrinsic utility from his top and distorted choice is 10,000 yuan and 6,000 yuan, respectively. The difference is 4,000 yuan, the size of the welfare loss. Subsidy is highly wasteful in this example: a lion's share of the subsidy is dissipated through the choice distortion.

The fact that the magnitude of the consumer welfare loss is solely determined by the gap in intrinsic utilities is crucial and highlights another important feature of our

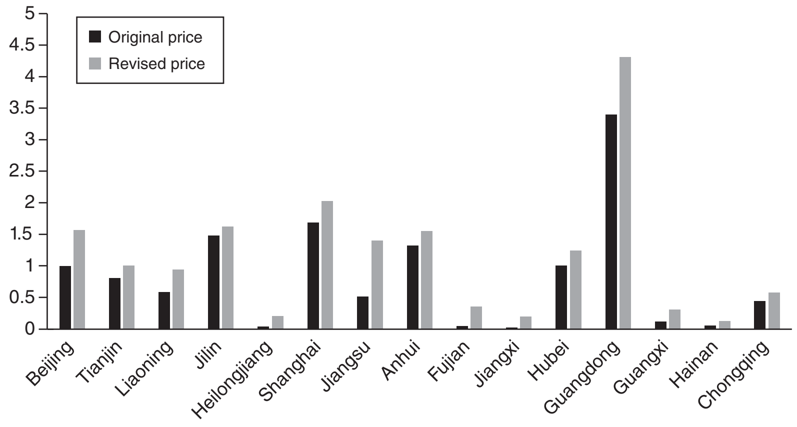

Figure 4. Consumer Welfare Loss Due to Local Protection, 2009–2011 (bn. Yuan)

Notes: Consumer welfare loss without price adjustment is the difference between consumers' monetized utility gain from protection and the cost of the subsidies. Price adjustment in response to local protection leads to bigger consumer welfare losses.

analysis: the size of consumer welfare losses is independent of the exact form of local protection, be it monetary subsidies or favorable treatment of local cars. In the example above, suppose that the local protection takes the form of quota restrictions instead of a monetary subsidy and consumer i chooses B over A in the presence of local protection. The welfare loss is again 4,000 yuan, the difference between her top choice and the distorted choice. As long as we could accurately estimate the extent of choice distortions, which is what the demand model does, our analysis will be able to capture the consumer welfare loss of local protection.

When prices are held fixed, consumer welfare loss is simply the difference in intrinsic utilities with or without distortion. Using simulations (and dropping subscripts m and t for notation simplicity), it is equivalent to

$$(10) \qquad \Delta(CS) = \frac{1}{NS}\sum_{i=1}^{NS}\frac{\left(\ln\sum_{j=0}^{J} e^{\bar{u}((1-\rho_j)p_j,X_j,\xi_j,D_i)} - \ln\sum_{j=0}^{J} e^{\bar{u}(p_j,X_j,\xi_j,D_i)}\right)}{\alpha_i}M - \sum_{j=1}^{J}\rho_j p_j s_j M,$$

where NS is the number of simulated households. The first term measures total monetized utility gain from local protection and the second term is the cost of these subsidies. Similarly, consumer welfare loss with price adjustments is given by:

$$(11) \qquad \Delta(CS)' = \frac{1}{NS}\sum_{i=1}^{NS}\frac{\left(\ln\sum_{j=0}^{J} e^{\bar{u}((1-\rho_j)p_j,X_j,\xi_j,D_i)} - \ln\sum_{j=0}^{J} e^{\bar{u}(p_j',X_j,\xi_j,D_i)}\right)}{\alpha_i}M - \sum_{j=1}^{J}\rho_j p_j s_j M,$$

Table 12—Incidence of Local Protection by Income Groups

Variable	<48k	48k–96k	96k–144k	≥144k	Total
Number of households	77%	17%	4%	2%	1.3 bill.
Number of cars bought	12%	29%	33%	26%	246 mill.
Monetized utility gain	4%	17%	30%	49%	28.9 bill.

Notes: We calculate the probability of vehicle purchase and monetized utility gain for each simulated household in our estimation sample and aggregate them by income groups.

where p_j' stands for the optimal price of product j in the absence of local protection. The difference between $\Delta(CS)$ and $\Delta(CS)'$ captures changes in consumer surplus induced by price adjustments.

Figure 4 plots total consumer welfare loss between 2009 and 2011 for the 15 provinces that have at least one local JV or SOE brand. The other 16 provinces (not shown) are affected by price adjustments only. The black bars stand for welfare loss directly from choice distortions, and the white bars add welfare loss from price increases. As expected, welfare loss is higher in larger markets such as Guangdong and in provinces that are home to more JV and especially SOE brands. For example, Anhui only accounts for 2.9 percent of total vehicle sales in China (it is ranked thirteenth out of 31 provinces) but experiences the fifth-highest consumer welfare loss since it is home to 2 of the largest SOE brands, Chery and Anhui Jianghuai (JAC Motors).

Choice distortions alone cost 12.6 billion yuan in consumer welfare between 2009 and 2011. Loss per distorted choice is around 17,640 yuan, which is 17.3 percent of the average price of an SOE brand and 9.3 percent of the average price of a JV brand. With the impact from price adjustments taken into account, total consumer welfare loss is around 21.9 billion yuan, or US\$3.4 billion. To put things into perspective, our estimates imply that the total benefit to local products from local protection, $\sum_j \rho_j p_j s_j M$, is equivalent to a subsidy of 50.8 billion yuan. Consumer welfare loss is sizable (41 percent) relative to the magnitude of these discriminatory policies.

Not only does local protection distort consumer choices, but it is also highly regressive. As shown in Table 12, the lowest two income groups account for 90 percent of the households and 40 percent of vehicle purchases and contribute to 44 percent of national personal income taxes but only enjoy 22 percent of the policy benefits.[36] This happens for three reasons. First, high-income households are more likely to buy cars and buy more expensive cars that are associated with larger discounts. Second, price increases induced by local protection offset a large fraction of the gains for price-sensitive poor households. Third, poor households are vulnerable to choice distortions because they are more likely to switch from not buying to buying some subsidized cars. In contrast, high-income households are more likely to choose the same JVs (or SOEs) with or without local protection. Local protection not only reduces aggregate consumer surplus through choice distortions, it also exacerbates inequality. Most of the policy benefits accrue to rich households that

[36] We first calculate each pseudo-household's personal income tax according to the tax law effective in China between March 2008 and August 2011 and then aggregate by income brackets.

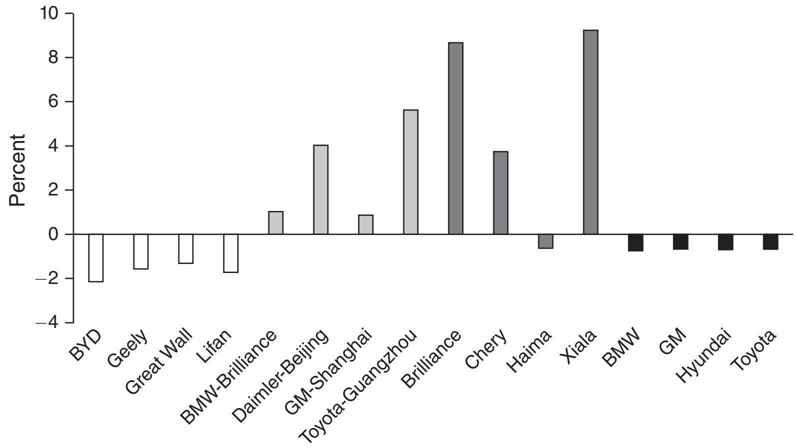

Figure 5. Impact of Local Protection on Firm Profits

Notes: We simulate a scenario without local protection and calculate the associated changes in profits for each firm. The first four firms are private, followed by four JVs, four SOEs, and four foreign firms, respectively.

are more likely to buy cars, are less likely to incur choice distortions, and suffer less from price increases.[37]

Turning to auto manufactures, Figure 5 illustrates the impact of local protection on profits for selected firms with different ownership (the first four firms are private firms, followed by four JVs, four SOEs, and four foreign firms, respectively). Local protection generally benefits JVs and SOEs at the expense of private automakers and imports, although there is considerable heterogeneity across firms. Among SOEs, Brilliance and Xiali enjoy an 8.7 percent and a 9.2 percent boost in total profits, respectively, while Haima incurs a net loss of 0.6 percent. The fact that some SOEs or JVs are hurt by local protection should not come as a surprise. Since Haima is based in a small island province that accounts for only 0.5 percent of national vehicle sales, Haima's losses in nonlocal markets dominate its gains in the headquarter province.

Because private firms are, on average, 7 percent more cost efficient than JVs and SOEs, local protection has long-term repercussions on production efficiency. The choice distortions induce production reallocation away from efficient private firms and toward JVs and SOEs, which translates into a cost increase of 206 million yuan for the industry. While the magnitude of this static impact is small, the long-term consequence could be significant, especially if some of the inefficient SOEs primarily survive through local protection.[38]

To quantify the impact of local protection on the aggregate producer surplus, we note that part of the profit increase arises from substitutions from the outside option: some consumers who bought a car because of the subsidies would have chosen the

[37] Local protection is still regressive even if modeled as a flat rebate, because low-income households account for 90 percent of the population but only 40 percent of purchase.

[38] For example, based on its annual reports, Xiali's net profits from auto production were 2.1 percent, 3.0 percent, and 1.5 percent in 2009, 2010, and 2011, respectively. It would have incurred heavy losses if not for the 8 percent profit boost due to local protection.

outside option otherwise. When a household does not buy a car, it could be spending money on taxi rides, public transportation, used cars, and other economic activities that generate profits. Such substitutions from the outside option lead to redistribution of producer surplus across industries. A precise statement of the impact of local protection on producer surplus across all industries is beyond the scope of our model. To facilitate comparisons with the consumer surplus, we report separately changes in profit that come from substitution between different vehicles (which only involves the auto industry) and those driven by substitution from the outside option (which also involves redistribution across industries).

When we exclude substitutions from the outside option, local protection increases total firm profits by 8.8 billion yuan. Sixty-seven percent of the profit gain (5.9 billion yuan) is due to the price hike induced by local protection, while the other 2.9 billion yuan is driven by net substitutions from cheaper to more expensive cars. Substitution from the outside option increases auto firms' profits by an additional 6.7 billion yuan.

Local protection raises local governments' tax revenue by 0.6 billion yuan. Another 4.1 billion yuan of tax revenue accrues to the central government.[39] Putting things together, we find that local protection results in a net loss of 8.4 billion yuan in social welfare between 2009 and 2011: the 21.9 billion yuan reduction in consumer welfare is only partially offset by an increase of 8.8 billion yuan in profit and 4.7 billion yuan in tax revenues.

C. *Incentives to Protect*

If local protection reduces social welfare and perpetuates production inefficiency, why does it persist? Our simulation demonstrates that without federal oversight, implementing some form of local protection is the dominant strategy for most provincial governments.

From a provincial government's perspective, implementing local protection leads to higher profits for firms based in its jurisdiction and a higher tax revenue, though it lowers consumer surplus due to choice distortions. All of these changes happen locally and are independent of policies in other provinces in the absence of price changes (because local protection does not affect profits in other provinces). Price adjustments in response to local protection, however, generate rippling consequences for all firms in all markets and complicate the welfare comparison significantly. In the analysis below, we shut down price responses, which are modest, as shown in Section VA.[40]

We start from an equilibrium without local protection; simulate changes in consumer surplus, profit, and tax revenue in each province when its provincial government

[39] Among the four types of taxes discussed in Section IIIB, value-added tax is split 25 percent versus 75 percent between local governments and the central government, while the other taxes (sales tax, consumption tax, and import tariff) are collected by the central government. The local government also collects corporate income tax at a rate of 40 percent, but most auto firms report minimal income.

[40] Allowing for price adjustment would strengthen local governments' private incentives to protect because it further raises local firms' profit. We do not consider price adjustment, because its magnitude is small. In addition, its exact impact depends on policy decisions by all other provincial governments, which is rather complex.

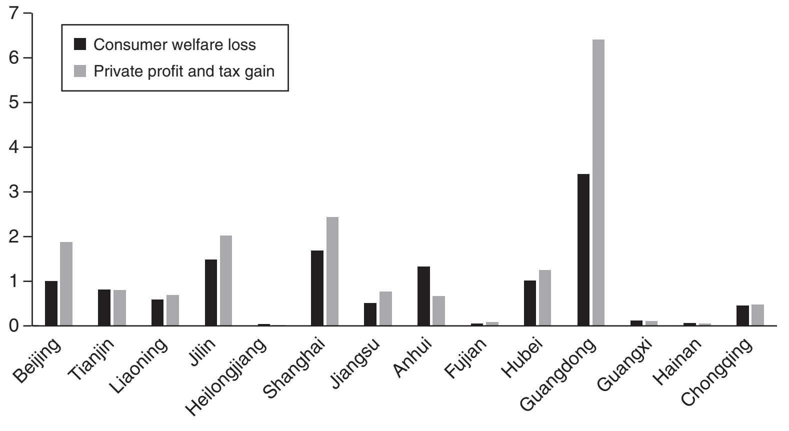

Figure 6. Benefits and Costs of Local Protection

Notes: We start from an equilibrium without local protection and simulate changes in consumer surplus, profit, and tax revenue in each province when its provincial government unilaterally introduces protection. We hold prices fixed at the levels without protection throughout.

unilaterally introduces protection; and plot the numbers in Figure 6. If provincial governments weigh consumer surplus, industry profits, and tax revenues equally, implementing local protection is the dominant strategy for all but Anhui province, which presents an interesting case. The two local SOEs in Anhui, Chery and JAC, mainly produce low-end vehicles that have thin profit margins. As a result, profits and tax gains induced by local protection are small and outweighed by consumer welfare loss. Our analysis indicates that it would have been welfare improving for Anhui to unilaterally remove its local protection.

The equilibrium outcome of each province protecting its local firms is suboptimal from a social planner's perspective, however, because local protection hurts other provinces. For example, protection in Shanghai increases local welfare by 0.7 billion yuan but reduces national welfare by 1.8 billion yuan. In the absence of central oversight that internalizes the cross-region business stealing, provincial governments end up in a prisoner's dilemma, and local protection persists to the detriment of overall social welfare.

D. *Discussion*

A few features of our welfare analysis are worth discussing. First, our model only allows local governments two choices: to protect at the estimated average intensity or to not protect at all. While we cannot estimate the level of protection separately for each province, our results show that no protection is a dominated strategy for all but one province. The fact that some province protects its local firms even though this *reduces* its provincial welfare underscores the strong incentives governments face in implementing discriminatory policies to protect local economy (firms).

Second, while we have focused on profits and tax revenue in our analysis, governments face other incentives to protect local firms. For example, local protection might create jobs. Using information on employment from the 2009 Annual Survey of Manufacturers conducted by the National Bureau of Statistics, we find that annual output per worker is 6.9 cars for an average SOE and 39.1 for an average JV.[41] A back-of-envelope calculation using results in Table 10 suggests that increases in local production would add 3,956 workers to local JVs and 11,063 workers to local SOEs. The effects decrease to 1,448 and 6,329 workers, respectively, when taking into account lost sales in other provinces. On net, this constitutes a 2.6 percent gain in employment in the local automobile industry, as the benefit is greatly diminished due to the negative effects of local protection on nonlocal firms. Relative to the magnitude of local subsidy, which we estimate is 25.4 billion if local protection involves subsidies 50 percent of the time, the gain in employment appears modest (each additional job costs more than 3 million yuan).

Third, we do not observe home bias directly but instead back out the magnitude of home bias using our demand analysis. Our model attributes all home bias not explained by vehicle attributes and consumer preferences to local protection. As a result, our local protection estimate includes nonpolicy factors that affect demand but are not adequately controlled in the empirical analysis. This would inflate the estimated welfare loss. On the other hand, there are reasons to believe that our estimates are conservative. For example, we abstract away from the welfare cost of tax collection that is necessary to finance subsidies. Assuming that the marginal excess burden is \$0.37 per yuan (Ballard, Shoven, and Whalley 1985) and that local protection involves subsidies 50 percent of the time, the welfare loss associated with financing these subsidies using taxes would amount to 18.8 billion yuan. Accounting for this would more than triple the net welfare loss of 8.4 billion yuan estimated above.[42] In addition, our analysis is partial and static: we exclude institutional purchases (which are subjected to even stronger protection), omit subsidies that auto firms receive during the production process, and do not take into consideration long-term consequences of local protectionism. Previous literature (Bronnenberg, Dubé, and Gentzkow 2012) has shown that consumers' preference are highly persistent. To the extent that past policies affect consumers' future choices through preferences, aggregate welfare loss could be considerably higher than what we present here.

VI. Conclusion

Based on the census of new passenger vehicle registrations in China between 2009 and 2011, we provide the first quantitative analysis of the intensity of local protectionism and its welfare consequences in the context of China's automobile industry. Local protection significantly reduces consumer welfare and is highly

[41] Average output-per-worker ratio in the European Union was 7.11 in 2013 according to a report by the European Automobile Manufacturers Association in 2017 (https://www.acea.auto/statistics/article/top-20-motor-vehicles-produced-per-worker-by-country). Output-per-worker ratio in the United States falls in the range between 40 and 60 in the past 10 years according to a 2019 report by the Federal Reserve Bank of St Louis (https://www.stlouisfed.org/on-the-economy/2019/april/us-auto-labor-market-nafta).

[42] According to Ballard, Shoven, and Whalley (1985), the welfare loss from non-lump-sum taxes is in the range of \$0.17 to \$0.56 per dollar of extra revenue in the United States. Our calculation above uses the midpoint of this range. Note that the marginal excess burden for tax collection is likely higher in China, since taxed activities tend to be more elastic, market distortions are more severe, and tax evasion is prevalent.

regressive. In addition, it perpetuates production inefficiency by benefiting high-cost JVs and SOEs at the expense of low-cost private firms. Local protectionism persists because of a prisoners' dilemma: while the society as a whole is better off in a world without local protection, local governments have no incentive to abolish local protection unilaterally. Our results suggest that effective oversight by the central government in eliminating interregional trade barriers would help market integration and improve social welfare.

Our study has focused on the short-run static impact of local protectionism on market outcomes and social welfare. Protective policies affect industry dynamics such as firm entry and exit, innovation, and productivity. These policies could also shape consumer preferences and influence consumer ethnocentrism in the long run. Future research could quantify these long-term consequences of local protectionism and examine the extent to which it has contributed to several salient features of China's automobile industry, such as low concentration ratio, geographically scattered production facilities, and low capacity utilization.

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