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QUID PRO QUO, KNOWLEDGE SPILLOVER, AND INDUSTRIAL QUALITY UPGRADING: EVIDENCE FROM THE CHINESE AUTO INDUSTRY

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ABSTRACT

While there is a vast body of research on the benefits of FDI in developing countries, whether and how the form of FDI matters have received limited attention. This paper studies the impact of FDI via quid pro quo (technology for market access) on facilitating knowledge spillover and quality upgrading. Our context is the Chinese automobile industry, where foreign automakers are required to set up joint ventures (the "quid") with domestic automakers in return for market access (the "quo"). The identification strategy exploits a unique dataset of detailed vehicle quality measures along multiple dimensions and relies on within-product quality variation across dimensions. We show that affiliated domestic automakers adopt more similar quality strength as their joint ventures, compared to non-affiliated pairs. The results suggest that quid pro quo generates additional knowledge spillover to affiliated domestic automakers, on top of any industry-wide spillover. We rule out endogenous joint venture network formation, overlapping customer bases, or direct technology transfer via market transactions as alternative explanations. Analyses leveraging additional micro datasets on worker flows and shared upstream suppliers among automakers demonstrate that labor mobility and supplier network are important channels in mediating knowledge spillover. On the other hand, while quid pro quo facilitates learning, such a requirement is not a prerequisite for knowledge spillover. Counterfactual exercises show that quid pro quo is not the primary driver of the overall quality improvement experienced by domestic automakers.

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1 Introduction

The past several decades have witnessed significant liberalization among developing economies to foreign trade and investment as advocated by various international organizations (UNCTAD, 2018; World Bank, 2018).[1] Nevertheless, emerging economies such as China, India, and Brazil continue to impose considerable restrictions on foreign direct investment (FDI) in certain sectors for strategic considerations. One such policy is "*quid pro quo*" (technology for market access), which requires multinational firms to form joint ventures (JVs) with domestic firms, often with a significant cap on foreign equity, in return for gaining access to the domestic market of the host country (Holmes, McGrattan, and Prescott, 2015).[2] While the joint venture requirement more directly exposes firms in developing countries to foreign technology, multinational firms consider it a form of coerced technology transfer and a significant barrier to investing in developing countries. *Quid pro quo* lies on the front line of the US-China trade debate, and concern over this policy was a key stated justification behind the Trump administration's decision to impose tariffs on $50 billion of Chinese imports in 2018.[3]

Despite the controversy surrounding *quid pro quo*, little is known about its benefits to the host country, compared to unrestricted FDI. The vast literature on FDI has paid relatively little attention to whether and how the *form* of FDI matters (see Harrison and Rodríguez-Clare (2009) for a review). In this paper, we attempt to fill the knowledge gap by examining the importance of the joint venture requirement under *quid pro quo* in facilitating knowledge spillover from foreign to domestic firms in developing countries. Unlike previous studies that mostly rely on firm-level TFP (i.e., the Solow residual) as the outcome measure, we exploit a rich set of direct measures of product quality that embody firms' fundamental technological capabilities. These quality measures give us a tangible way of measuring knowledge spillover and allow us to look inside the black box of TFP. Understanding the determinants of quality upgrading, an important engine of economic growth, is also a first-order question for both academics and policy makers in developing countries (Verhoogen, 2020).

Our context is the Chinese automobile industry, where *quid pro quo* was first introduced in the country and henceforth became a major industrial policy. Foreign automakers are required to set up joint ventures (the "*quid*") with domestic automakers in order to produce and sell cars in China (the

[1] Restrictions on foreign investment and technology transfer were common in developing and even OECD countries before the 1990s. Economic and trade liberalization in the 1980s and 1990s brought about a more laissez-faire attitude toward foreign investment and technology transfer, and many restrictions were removed during that period (Karabay, 2010).

[2] China keeps a 50% foreign ownership cap in 38 "restricted access" industries. Vietnam has a 49% foreign ownership cap for all publicly listed companies. The Philippines has a 40% foreign ownership cap on telecommunication and utility companies. In India and Brazil, foreign ownership was restricted in numerous key industries until recently.

[3] The Office of the US Trade Representative (USTR) issued a report in 2018 on its investigation into China's policies and practices related to technology transfer, intellectual property, and innovation. Forced technology transfer using foreign ownership restrictions is considered a key component in China's technology transfer regime. Source: https://ustr.gov/sites/default/files/Section 301 FINAL.PDF.

"*quo*"). A fixed cap of 50% is imposed on foreign ownership share, and it is binding in all cases. China has been the largest automobile market in the world since 2009. All major multinational automakers compete in this large market, including 23 JVs (e.g., BMW-Brilliance), 12 domestic automakers that are affiliated with the JVs but have independent production (e.g., Brilliance Auto),[4] and 7 domestic automakers without any JV affiliation (e.g. BYD).

The automobile industry is a classical industry for studying knowledge spillover given the multitude of technologies embodied in the final products, including propulsion, electronics, safety, fuel efficiency, emission control, materials, and most recently AI. In recent years, Chinese domestic automakers have developed high-quality indigenous brands, potentially benefiting from knowledge spillover from foreign automakers via the JVs. The rich industry dynamics allow us to study the following questions: Has the ownership affiliation stipulated under the *quid pro quo* policy been effective in inducing knowledge spillover from foreign automakers to domestic automakers? If so, to what extent, and what are the underlying mechanisms? What will happen if *quid pro quo* is lifted - a question that speaks directly to the current trade debate between the US and China?

To answer these questions, we have compiled to our knowledge the most comprehensive data on China's automobile industry. Our primary dataset consists of direct observations of quality along multiple dimensions of vehicle performance for nearly the universe of car models produced in China from 2009 to 2014.[5] We map the rich and granular quality data on to the entire ownership network to trace out the patterns of knowledge flow. We further complement the quality and ownership information with production location for each car model, patent transfers between JVs and domestic automakers, worker flows among automakers, and information on upstream parts and components suppliers to examine alternative explanations and potential channels of knowledge flow.

We begin by documenting descriptive patterns of quality catch-up of Chinese domestic automakers. The malfunction rates of car models produced by both affiliated and non-affiliated domestic automakers were cut in half in less than a decade from 2009 to 2014, demonstrating an impressive record of quality improvement. At the same time, the quality gap between domestic models and JV models produced in China has greatly narrowed: the malfunction rate of domestic models was twice as high as that for JVs in 2009. By 2014, the gap has shrunk to 33 percentage points.

While many factors may explain the overall quality upgrading of the industry, including industry-wide spillovers due to the presence of foreign automakers, we focus on the role of *quid pro quo*. The joint venture requirement creates a set of domestic automakers that are affiliated with foreign automakers

[4]Brilliance Auto is the domestic partner of BMW and owns 50% of the equity of the JV, BMW-Brilliance. The JV produces BMW models that are sold in China. At the same time, Brilliance Auto has its own independent production facilities and produces indigenous models under the Brilliance brand.

[5]The data are sourced from J.D. Power, a leading marketing firm best known for its research on quality rankings of automobile vehicles. These measures are widely regarded as industry standards: https://www.vox.com/the-goods/2018/11/27/18105479/jd-power-car-commercials.

through the JVs. These domestic automakers are the primary beneficiaries of the policy, with direct access to foreign technology.[6] Therefore, to isolate knowledge spillover as a result of ownership affiliation under *quid pro quo*, we examine whether the affiliated domestics automakers ("followers") learned more from their affiliated foreign automakers ("leaders") compared to non-affiliated domestic automakers.

The key identification challenge is the potentially endogenous JV formation whereby foreign and domestic automakers strategically choose each other as partners based on quality. This type of sorting, positive or negative, could confound the estimated spillover effect. Our analysis takes advantage of detailed quality measures along multiple dimensions and exploits *within-model* relative strength across dimensions. Specifically, we examine whether affiliated domestic followers adopt the quality strength of the JV leaders in their independent production. An example helps illustrate our empirical strategy. BMW-Brilliance, a JV between the German automaker, BMW, and the domestic automaker, Brilliance, produces BMW models that have strong engine performance. Nissan-Dongfeng, a JV between the Japanese automaker, Nissan, and the domestic automaker, Dongfeng, produce Nissan models that are fuel efficient. We examine whether Brilliance produces indigenous models that have good engine performance, and Dongfeng sells models that are fuel efficient, relative to their average quality.

Our empirical framework forms an exhaustive list of pairs between domestic models and JV models and regress the quality of a domestic model in a specific dimension on the quality of a JV model in the same dimension. To account for the endogenous formation, the main specification controls for the *overall* quality of each model in each period. In addition, it also controls for industry-wide technology progress in different quality dimensions (e.g., fuel-saving technologies) and quality strength common across vehicle segments (e.g., better safety features in luxury segment).[7] We find that when a JV model scores one standard deviation higher in a quality dimension, indigenous models by its affiliated domestic automaker in the same vehicle segment score 0.138 standard deviation higher in the same dimension, relative to models by other domestic automakers.

While our main specification addresses JV formation based on the *overall* quality level, one may still be concerned about endogenous formation based on *relative* strength. For example, domestic automakers may seek foreign partners that have strength in certain quality dimensions to compensate their weakness or augment their advantage. To address this issue, we first exploit an institutional feature by limiting our sample to JVs formed prior to 2000. At that time, China's passenger vehicle market was in its infancy. Most of the domestic automakers had very limited technological know-how in passenger vehicle production. Therefore, it is unlikely that partners of JVs were matched based on quality strength. Nevertheless, the pattern of shared quality persists for this sub-sample. Second, we

[6] As a common practice under *quid pro quo*, foreign automakers offer existing product lines and knowhow as equity while domestic partners provide capital and manufacturing facility when setting up a JV.

[7] Following the standard classification system, we classify models into eight segments: mini sedan, small sedan, compact sedan, medium sedan, large sedan, small-medium SUV, large SUV, and MPV. Quality is measured in different dimensions such as engine, transmission, and interior, to be discussed below.

directly control for any initial correlation in quality strength between followers and leaders by partialling out model by quality dimension fixed effects and only exploit temporal co-movement in quality measures between the pair. Our results survive this more demanding specification.

In addition to endogenous JV formation, another confounding factor that may lead to shared quality strength between JVs and affiliated automakers is that both groups might target the same set of consumers and hence design similar products. However, analyses using the household vehicle ownership surveys indicate that models by JVs and affiliated domestic partners are not considered as close substitutes by most car buyers. JVs models are concentrated in the high-end markets, while indigenous brands produced by domestic automakers tend to target the low-end market. Lastly, the observed patterns of knowledge spillover might be driven by market transactions, such as patent licensing and assignment. Using records from the universe of patent applications and transfers, we find *no* patent transfer activity from JVs to affiliated SOEs during our sample period.

Having demonstrated the presence of knowledge spillover from JVs to their affiliated automakers, we consider two potential mechanisms for knowledge spillover, worker flows and supplier network, both of which have been documented in the literature. As carriers of technology know-how, workers move across automakers and serve as a conduit of knowledge spillover.[8] We construct worker flows between each pair of JV and domestic automakers using data from LinkedIn (China), whose number of users in the auto industry closely mimics the local volume of auto production. We find higher rates of worker flows between affiliated pairs than non-affiliated pairs. The flows from JVs to affiliated domestic automakers, rather than the reverse, are associated with knowledge spillover. In addition, high-tech workers (engineers and designers) appear more relevant for knowledge spillover, though the estimate is insignificant. These findings corroborate well the results in the existing literature and are consistent with anecdotal evidence that domestic automakers benefit from recruiting talents from foreign automakers with advanced technology. Worker flows that domestic automakers receive from affiliated JVs explain 58% of knowledge spillover via ownership affiliation.

The second mechanism that we investigate is motivated by the observation that high-quality parts and components directly affect the overall performance of the downstream product. JVs' high quality standards for their suppliers in the host country often enhance the performance of the latter. If the affiliated domestic automakers source from the same set of part suppliers that serve JVs, they could directly benefit from the 'shared supplier spillover' (Kee, 2015).[9] Using the supplier network data

[8]Studies that document the role of worker flows in transmitting knowledge between firms include Castillo et al. (2020); Stoyanov and Zubanov (2012a); Maliranta, Mohnen, and Rouvinen (2009); Boschma, Eriksson, and Lindgren (2009); Møen (2005), and between foreign multinationals and domestic firms include Balsvik (2011); Görg and Strobl (2005); Poole (2013); Fosfuri, Motta, and Rønde (2001).

[9]There exists a large body of work documenting the positive impact of trade and FDI on the development of the local intermediate inputs market and spillover via backward linkages (e.g., Javorcik (2004); Blalock and Gertler (2008); Javorcik and Spatareanu (2008); Havranek and Irsova (2011); Gorodnichenko, Svejnar, and Terrell (2014); Kee (2015); Eslava, Fieler, and Xu (2015); Kee and Tang (2016)).

from MarkLines, which provides online information services for the automobile industry, we calculate the number of common part suppliers shared by pairs of JV and domestic models. JVs and affiliated domestic firms have a significantly greater supplier overlap, which contributes to 32% of knowledge spillover via ownership affiliation.

Finally, we turn to the policy question of what would happen to domestic automakers' quality if *quid pro quo* were lifted in 2009, the beginning of our sample period. First, we conduct several additional reduced form analyses to shed light on whether ownership affiliation stipulated by the *quid pro quo* policy is a prerequisite for knowledge spillover. By exploiting the partial overlap in ownership and geographic networks, we show that while spillover is the strongest between affiliated JV-domestic pairs in the same city, there exists sizeable knowledge spillover from JVs to non-affiliated automakers located in the same city. Such spillover from JVs to non-affiliated automakers persists even in cities without any affiliated domestic automakers. Together, these results suggest that ownership affiliation, as required by *quid pro quo*, is not a necessary condition for knowledge spillover, and the presence of affiliated domestic partners is not a necessary "conduit" for knowledge to flow from foreign to domestic automakers. Evidence from the upstream parts and components industry further shows that ownership affiliation does not confer significant advantage in terms of knowledge spillover compared to full foreign ownership.

We end with a quantification exercise where we remove *quid pro quo* and simulate the quality evolution of domestic models. Ceteris paribus, lifting *quid pro quo* in 2009 would have reduced the quality improvement experienced by domestic models by 5.7% to 16.5%. The results suggest that *quid pro quo* is not the primary driver of quality upgrading in our setting, partly because knowledge spillover and learning could happen through other channels even if foreign automakers were to operate as wholly owned companies. These findings speak directly to the current US-China trade debate. Amid recent tensions with the US regarding forced technology transfers via the *quid pro quo* policy, the Chinese government has pledged to remove the foreign ownership requirement in several strategic sectors, including the auto industry, by 2022. Our findings suggest that doing so would not significantly hinder the upgrading of the domestic industry.

It is important to acknowledge several caveats of our analyses. First, our study focuses on the benefits of *quid pro quo* to domestic firms, but does not speak about the costs to foreign firms, both in terms of the profit split and potential IP risks. Understanding the former takes us one step closer to evaluating the full costs and benefits of the policy, and thereby its current relevance. Second, and relatedly, our analysis focuses on spillover to domestic automakers *conditioning on* the existing set of products and technologies introduced by foreign automakers. Future work is needed to examine foreign automakers' incentives to introduce products and technology in light of global knowledge spillover (Buera and Oberfield, 2016; Bilir and Morales, 2016). Finally, the data coverage prevents us from evaluating the historical efficacy of *quid pro quo*, i.e., what would have happened if China did not have the policy from the beginning. It is conceivable that market-for-technology policies are more effective as an infant industry takes off and less effective when the industry matures.

Our study contributes to several strands of literature. While there is an extensive empirical literature on FDI spillover (see Harrison and Rodríguez-Clare (2009) for a recent review), whether and how the form of FDI affects quality upgrading in the host country has received relatively little attention (Blomström and Sjöholm, 1999; Aitken and Harrison, 1999; Javorcik, 2004; Javorcik and Spatareanu, 2008; Fons-Rosen et al., 2013). Our study shows that while *quid pro quo* facilitates knowledge spillover, it is not the primary driver of quality upgrading among domestic automakers in our setting.

Second, most of the FDI literature relies on industry-level variation in FDI presence or intensity to identify the impact on the host country (e.g., Haddad and Harrison (1993); Aitken and Harrison (1999); Javorcik (2004); Keller and Yeaple (2009)). However, entry of foreign firms could be endogenous to unobserved industry-level shocks, such as changing demand conditions and government policies, which may directly affect the performance of domestic firms in the same industry. In addition, many studies focus on TFP improvement as the key outcome variable (e.g., Haskel, Pereira, and Slaughter (2007); Keller and Yeaple (2009); Abebe, McMillan, and Serafinelli (2018)), which reflects both the positive spillover effect and the negative competition effect (Kosova, 2010; Lu, Tao, and Zhu, 2017; Fons-Rosen et al., 2017). We contribute to the literature by using direct measures of quality at the product level that embed firms' technological capability. Our identification relies on within-product (i.e., vehicle model) quality strength, enabling us to control for industry-wide and firm-level potential confounds that might be correlated with the joint-venture formation. In addition, we shed light on the potential mechanisms of knowledge spillover, which remains relatively understudied in the literature (e.g., Balsvik (2011); Poole (2013); Kee (2015); Newman et al. (2015)). Our results highlight worker flows and supplier network as two important pathways of knowledge flow from foreign to domestic firms.

Third, our paper relates to the growing body of work in trade and development that aims at understanding the importance of technology innovation and quality upgrading in economic growth, especially in developing countries (see Verhoogen (2020) for an excellent review). The existing literature mostly focuses on indirect measures of technology and quality improvement, such as market shares and prices (Khandelwal, 2010), as quality is rarely observed in standard firm surveys. Our study adds to a nascent literature leveraging detailed quality measures for specific industries (e.g., Atkin, Khandelwal, and Osman (2017); Medina (2017)) to examine the impact of FDI on innovation and product quality.

Lastly, this research relates to an emerging literature on understanding the impacts of industrial policies on firm behavior, innovation, and economic growth (e.g., Kalouptsidi (2017); Igami and Uetake (2019); Chen and Lawell (2019); Chen et al. (2019); Barwick, Kalouptsidi, and Zahur (2019)). Our analysis allows us to examine the role of China's longstanding but controversial *quid pro quo* policy in an important industry (Holmes, McGrattan, and Prescott, 2015; Howell, 2018; Jiang et al., 2018).

The remainder of the paper is organized as follows. Section 2 discusses the industrial background and data. Section 3 illustrates the empirical strategy. Section 4 presents the main empirical results and robustness checks. Section 5 investigates the mechanisms. Section 6 discusses policy implications and performs a quantification exercise. Section 7 concludes.

2 Background and Data

2.1 The Chinese Auto Industry and *Quid Pro Quo*

When China started its reform and open-up policy in 1978, China's automobile manufacturing was concentrated in heavy trucks and buses with virtually no production capacity of passenger cars. To develop its domestic passenger car sector, the Chinese government allowed international automakers to enter but required them to partner with domestic automakers to set up a production facility. In forming joint ventures (JVs), foreign automakers offer know-how and product lines as equity, which is capped at 50%, while domestic automakers provide manufacturing facilities and labor.[10] *Quid pro quo* is implemented in many industries that are considered strategically important, from advanced manufacturing such as aircraft and shipbuilding to service sectors such as banking and higher education. There are at least two rationales for the policy. The first is to protect young and small domestic producers in nascent industries (i.e., the infant industry argument). The second is to enhance domestic technical capabilities and allow domestic firms to learn from their foreign partners.

The first joint venture for automobile manufacturing was set up in 1983 between American Motors Corporation (AMC, later acquired by Chrysler Corporation) and Beijing Automotive Company (now Beijing Automotive Industry Corporation, BAIC) to produce the Jeep models. In 1984, Volkswagen joined with Shanghai Automotive Company (now Shanghai Automotive Industry Corporation, SAIC) to form VW-SAIC. In the early years, foreign automakers used joint ventures as a strategy to avoid the high tariff of around 250% at that time. The majority of manufacturing activities were made up of "knock-down kit" assembly. As a result, technology transfer was limited.

Prior to 2000, most of the affiliated domestic automakers relied on the JVs for production of passenger vehicles.[11] There were few indigenous brands in the country, as shown in Appendix Figure B.1. In 2004, the central government announced an explicit goal of developing domestic automotive tech-

[10] In 1978, China's First Ministry of Machinery, in charge of automobile production, invited major international automakers to visit China and negotiated with them terms on technology transfer with the goal of developing the domestic auto industry. GM was the first to send a delegation to China in October 1978 and met with the Vice Premier Li Lanqing. During the meeting, GM CEO Thomas Murphy put forward the idea of a joint venture, which was a foreign concept to the Chinese hosts. Using joint ventures to incentivize foreign automakers to provide technology was quickly reported to the pragmatic leader Deng Xiaoping, who supported the idea. It then became a long-standing policy. Source: https://media.gm.com/media/cn/zh/gm/news.detail.html/content/Pages/news/cn/zh/2011/Aug/0802.html.

[11] SAIC stopped producing its own indigenous brand SH760 in 1991, after the joint venture with VW became very successful. See https://www.autohome.com.cn/culture/201212/440381-5.html.

nology and promoting indigenous brands through supporting the establishment of R&D facilities using tax incentives. The 2009 Automotive Adjustment and Revitalization Plan encouraged mergers and the reorganization of automobile firms and called for the creation of new indigenous brands, both for export and domestic sales. Under these government policies, affiliated domestic automakers started to launch their own brands of passenger vehicles. For example, SAIC launched Roewe, and FAW launched its first indigenous brand, Besturn, both in 2006. Dongfeng built its own assembly plants in 2007 and introduced its first indigenous model in 2009. By 2014, the affiliated domestic automakers had caught up with non-affiliated domestic automakers in product offering.

Figure 1 presents a snapshot of the ownership network for the Chinese auto industry as of 2014. Many international automakers formed multiple joint ventures with different domestic partners and vice versa. For example, in addition to VW-SAIC, Volkswagen partnered with First Automobile Works Group (FAW) to form VW-FAW in 1991. At the same time, one domestic firm can have multiple foreign partners. In total, there are seven big affiliated groups, as shown by the dotted blocks in Figure 1. To avoid complications in intellectual property rights, foreign automakers transfer the production line of a given brand exclusively to one domestic partner. For example, VW-SAIC produces Passat and Tiguan, while VW-FAW sells Audi and Jetta. There is no product-line overlap between any pair of JVs. All of the affiliated domestic automakers during our sample period are state-owned enterprises (SOEs). The non-affiliated domestic automakers (those without foreign partners) include both SOEs and private firms. They constitute the category of non-affiliated domestic automakers throughout this paper.

The industry has witnessed unprecedented growth after China entered the WTO in 2001. Sales of new passenger vehicles increased from 0.85 million units in 2001 to 24.7 million units in 2017, surpassing the US in 2009 to become the world's largest market.[12] In 2017, China alone accounts for more than 33% of the global auto production and sales. The industry is highly competitive and consists of 48 firms with production exceeding 10,000 units in 2014. The number of JVs has also steadily increased (Appendix Figure B.2): by 2009, most of the major international automakers have launched JVs in China. Appendix Table B.1 lists the JVs and their sales and market shares in 2014. While the JVs have been dominating the industry, sales of domestic firms have also been growing over the past decade (Figure B.3). This is especially true in the SUV segment, where the market shares by domestic firms grew from 27% to 36% between 2009 and 2014.

Under the terms of WTO, explicit technology transfer requirements for market access are not permitted. Hence *quid pro quo* in China has been mostly carried out implicitly via ownership restrictions on joint ventures to facilitate technology transfer from the foreign firms. It is considered by some countries as part of China's broad industrial policy that creates unfair advantages for its domestic companies. Because of the emphasis on technology transfer, this policy is criticized as state-sponsored efforts to

[12] Passenger vehicles in China include sedans, sport utility vehicles (SUVs), and multi-purpose vehicles (MPVs). Minivans and pickup trucks are considered commercial vehicles.

systematically pry technology from foreign companies. According to the 2018 China Business Climate Survey Report conducted by the American Chamber of Commerce, 21% of 434 companies surveyed in China faced pressure to transfer technology. Such pressure is most often felt in strategically important industries such as aerospace (44%) and chemicals (41%).[13]

Amid recent trade tensions with the US, the Chinese government pledged to further open up its automobile market through lifting the foreign ownership cap by 2022, representing a major shift from the *quid pro quo* policy in place for around four decades. This effectively allows foreign automakers to have solely owned production facilities in China. Following the pledge, BMW and its domestic partner Brilliance reached an agreement where BMW pays Brilliance $4.1 billion for a 25% stake in the joint venture to increase BMW's ownership share to 75% by 2022.[14] Many have speculated that this could have a profound impact not only on the Chinese market but also on the global industry. Understanding the role played by ownership affiliation serves as a crucial step in understanding the implications of removing *quid pro quo*.

2.2 Data

Our empirical analysis benefits from a multitude of datasets on the Chinese auto industry. We describe each of them in detail below.

Vehicle quality measures Quality measures come from the annual Initial Quality Study (IQS) and Automotive Performance, Execution and Layout Study (APEAL) that are conducted by JD Power between 2009 and 2014. Between April and June each year, JD power recruits subjects who have purchased a vehicle for less than a year in over 50 cities in China, and surveys their user experience during the first six months of vehicle ownership. The survey covers major passenger vehicle models in China, accounting for over 9% of market shares in terms of sales in 2014. The total number of survey correspondents in 2014 is 18,884, or around 110 car owners per model. The IQS study reports the number of problems experienced per 100 vehicles during the first 90 days of ownership. The survey asks 227 questions, covering a complete spectrum of vehicle functionalities, which are aggregated to nine quality dimensions: exterior problems, driving experience, feature/control/displays, audio/entertainment/navigation, seat problems, HVAC problems, interior problems, and engine and transmission.[15] Industry experts believe that initial quality is an excellent predictor of long-term reliability, which has a significant impact on owner satisfaction and brand loyalty.

[13]Source: http://www.iberchina.org/files/2017/amcham_survey_2017.pdf.

[14]Shares of Brilliance traded in Hong Kong plunged 30% after the news of the agreement as the joint venture accounted for the majority of Brilliance's profit in 2017. The shares of other Chinese automakers also fell from the concern that their foreign partners may also increase the control of the joint ventures.

[15]IQS includes questions such as "Engine doesn't start at all" (engine), "Emergency/parking brake won't hold vehicle" (driving experience), and "Cup holders - broken/ damaged" (interior).

The APEAL study elicits user satisfaction ratings over 100 vehicle quality attributes, which are grouped to ten performance dimensions: interior, exterior, storage and space, audio/entertainment/navigation, seats, heating/ventilation/air-conditioning, driving dynamics, engine/transmission, visibility and driving safety, and fuel economy.[16]

Figure 2 presents the residualized figures on vehicle prices and the two quality measures. Panel A plots prices against IQS, with the left figure controlling for vehicle size and horsepower/weight (proxy for acceleration) and the right figure further controlling for year fixed effects, segment fixed effects, and ownership type fixed effects. Panel B shows the relationship between prices and APEAL with the same controls as in Panel A. The remarkably tight correlations between price and IQS/APEAL provide strong evidence that IQS and APEAL are reliable measures of vehicle quality, with high quality car models consistently commanding high prices.

Worker flow To examine worker mobility, we collect data on the employment history for all past and current employees in the Chinese auto industry who are registered on LinkedIn (China). The data contains 52,898 LinkedIn users who have worked in 60 JVs and domestic firms. The spatial distribution of these users is consistent with the spatial distribution of automobile production: the correlation coefficient between the number of LinkedIn users in a province and the provincial automobile production in 2018 is 0.89. The two provinces with the largest auto production, Guangzhou and Shanghai, also have the highest number of users in our data.[17] One might be worried that workers from affiliated automakers and those from non-affiliated automakers may have different a propensity to use LinkedIn, and hence create a selection issue. Among LinkedIn users in our data, the ratio of users from affiliated automakers to non-affiliated automakers is 0.95, compared to the ratio of vehicle sales of 1.12 between these two types of automakers in 2014.

We identify 4,099 users who have moved at least once from one automobile company to another. For each job switch, we compile information on firm name and location before and after the switch, as well as worker characteristics such as current occupation and education level. The majority of workers who changed jobs switched once (81%) or twice (16%). Our final sample covers 3,086 job switches after dropping observations with missing location data. 617 of them moved from JVs to domestic firms. The data allow us to examine worker flows as a mechanism of knowledge spillover.

Supplier network Data on the auto-part supplier network is compiled from Marklines' Who Supplies Whom database.[18] Our final sample covers 1378 distinct part suppliers, 271 vehicle parts under 31 part

[16]The APEAL study includes questions such as "smoothness of gearshift operation" (engine/transmission), "braking responsiveness/effort" (driving dynamics), and "interior materials convey an impression of high quality" (interior).

[17]Ge, Huang, and Png (2020) found that LinkedIn provides more accurate measures of worker mobility than commonly used patent databases.

[18]Marklines collects the supplier information in a number of ways. Some information is directly sourced from supplier companies or downstream assembly firms. Some is obtained from vehicle tear-downs where supplier information is retrieved

categories, and 459 vehicle models.[19] Since data at the annual level is sparse, especially in early periods of our sample, we pool information from all years to construct the supplier network. Each auto-part company supplies on average 2.8 parts to 11 vehicle models, and there is a small number of large suppliers that cover many parts and models. For an average model, we have supplier information on 39 vehicle parts. While the data is not complete enough to be regarded as a census of suppliers, it provides valuable information on the production network and captures the major suppliers for many models.

Geographical network We identify the plant location of each model using information from official websites of the auto firms (Table B.2). Figure B.4 maps vehicle models to their production cities. Each circle represents a city. Colors of the circle indicate the ownership composition of all the models produced in a given city. There is a partial overlap between the ownership network and location network. For example, DongFeng, one of the largest affiliated SOE firms, has a plant that located in the same city, Wuhan, as one of its JVs' plants (Honda-Dongfeng). It also has a plant in Liuzhou that does not host any of its JVs. At the same time, Geely, a private firm without any JV affiliation, has a plant in Shanghai that hosts two joint ventures (VW-SAIC and GM-SAIC). Our empirical analysis explores this partial overlap between ownership and geographical networks to assess whether ownership affiliation is a prerequisite for knowledge spillover.

Patent database Data on patent transfers and licensing is collected by China's State Intellectual Property Office and cover the universe of patent transfers between any firms up till the most recent year. There are two types of transactions: patent licensing and patent assignment. The former is a permission from the patent owner to use the licensee for a fee or royalties during a specified time period. The latter is a permanent transfer of the intellectual property right from the owner to the assignee for a payment. This information allows us to examine the extent of market-based direct technology transfers between JVs and domestic firms.

Household vehicle ownership survey Finally, we complement the above data sets with a large nationally representative household-level survey conducted annually by the China National Information Center from 2009 to 2014. Each household in the survey reports the vehicle purchased and alternative models considered. We use these choices to assess whether JVs and affiliated SOEs serve consumers with correlated preferences for quality.

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from the label or stamp on vehicle parts. Press releases and news articles are another important source.

[19]For example, part categories include the ventilation system, the engine's lubrication system, interior accessories, exterior accessories, etc. A part category contains multiple parts. For example, the lubrication system of the engine includes a sump, oil galleries, oil pump, and a filter.

2.3 Descriptive Patterns of Quality Upgrading

We begin by documenting descriptive patterns of quality upgrading across ownership type. JD Power's raw IQS scores report the malfunction rates of parts and components and represent an objective measure of vehicle performance. Panel A of Table 1 reports the summary statistics of IQS scores by year and ownership type for each of the nine quality dimensions. Two important patterns emerge. First, vehicle models produced by JVs have significantly higher quality than those by domestic firms in all quality dimensions in 2009. Second, vehicle quality has improved overall for both JVs and domestic models, but the improvement among domestic models has been more pronounced.

Figure 3 plots the dramatic improvement in the overall IQS score over time, summed across all nine quality dimensions, for JVs, affiliated SOEs, and non-affiliated domestic automakers, respectively (note that a smaller number of defects indicates higher quality). In 2009, JVs have significantly higher quality than the other two types: the number of defects per 100 vehicles was 143 for JV models, in contrast to 236 for models produced by affiliated domestic firms and 271 for those produced by non-affiliated domestic firms. By 2014, the overall IQS score of the domestic models has largely converged to that of the JVs': the number of defects per 100 vehicles is 94 for JV models, 123 for models by affiliated domestic firms, and 134 for those by non-affiliated automakers. We observe similar convergence patterns in each of the quality dimensions as shown in the second and third graphs of Figure 3. Our empirical strategy seeks to isolate the role of ownership affiliation under *quid pro quo* in driving the quality improvement of domestic models.[20]

Our second quality measure, APEAL scores, represents a more subjective evaluation of the driving experience. Panel B of Table 1 displays summary statistics of APEAL scores by year and ownership type. The change in APEAL scores over time is modest, in contrast to the significant improvement in IQS scores. The comparison highlights that APEAL scores, measuring consumer satisfaction, may be affected by consumer perception and could evolve over time as consumers become more knowledgeable about quality. For example, owners of luxury models may have a higher expectation than owners of entry models, which could be reflected in their evaluations. Our empirical analysis addresses this issue by including a rich set of fixed effects (model by year, car segment by quality dimension, and quality dimension by year) to capture the difference in consumer perceptions across models and over time and only relying on *within-model* perceptions across different quality dimensions. We also perform robustness checks using IQS and APEAL scores separately and obtain very similar results.

Since the raw IQS and APEAL scores (the malfunction rates) differ substantially in magnitude

[20]It is tempting to conclude from Figure 3 that ownership affiliation does not matter since both affiliated and non-affiliated domestic firms experienced rapid quality catch-up. However, given that all of the affiliated automakers are SOEs and the majority of the non-affiliated ones are private, it is difficult to draw conclusions from the observation data given how different the two groups of firms are in terms of organizational structure, efficiency level, competition incentives and growth dynamics (e.g., Song, Storesletten, and Zilibotti (2011); Brandt et al. (2017)).

across different quality dimensions, we separately standardize the responses for each of the 227 IQS survey questions and 100 APEAL questions using all model-year observations. Then we aggregate the standardized z-scores to the nine IQS dimensions and ten APEAL dimensions as listed in Table 1. Appendix Table B.3 reports the summary statistics for the standardized scores in each dimension. We observe similar patterns of catch up and convergence in most quality dimensions. Note that there is significant heterogeneity in quality performance across different dimensions among firms within an ownership type, a key source of variation we exploit in our empirical strategy.

3 Empirical Strategy

3.1 Empirical Framework

The goal of our empirical analysis is to identify knowledge spillover induced by the stipulated ownership affiliation under *quid pro quo* on top of any industry-wide learning and quality improvement due to the presence of foreign firms. Therefore, we look for differential spillover from JVs to affiliated domestic firms, relative to the spillover received by non-affiliated domestic firms. As knowledge spillover is rarely observed, we use similarity in product quality strength as evidence of knowledge spillover. For example, German brands such as BMW, Mercedes Benz, and Volkswagen are often associated with high quality in engine, driving dynamics, and safety dimensions. If models produced by affiliated domestic automakers exhibit higher quality measures in these same dimensions than non-affiliated models, ceteris paribus, we take this as an indication of knowledge spillover via the ownership affiliation.

However, the complicated ownership structure as discussed in Section 2.1 among JVs and domestic partners poses a significant challenge to our empirical analysis. Take First Auto Works as an example. It has a JV with three foreign firms: VW, Toyota, and Mazda. While VW is known for its engine power and reliability and Toyota is better at fuel efficiency, the average quality among cars produced by both VW and Toyota does not reflect the quality strength of either firm. In addition, the quality scores averaged over all foreign partners of an affiliated domestic firm masks the significant heterogeneity among different products across firms.

To address this issue, we exploit quality variation across different dimensions at the *model-pair* level. To ease the interpretation, we multiply the raw IQS scores by negative one, so that a larger IQS number (e.g., a less negative number) implies better quality (fewer defects), as does APEAL. We proceed in two steps. First, we construct the residualized (i.e., relative) quality strength for model i in vehicle segment s for quality dimension k in year t by partialling out fixed effects for model-year it (e.g., BMW-Brilliance X3 in 2014), segment-dimension sk (e.g., engine of small-medium SUV), and dimension-year kt (e.g., engine in 2014):

$$\text{Score}_{ikt} = \lambda_{kt} + \lambda_{sk} + \lambda_{it} + \widetilde{\text{Score}}_{ikt} \tag{1}$$

The rich set of product level and temporal fixed effects in Equation (1) helps mitigate common unobservables that affect quality improvement. Quality dimension by year fixed effects (λ_{kt}) control for dimension-specific time trends, such as an industry-wide improvement in the power train or the navigation system over time. Segment by dimension fixed effects (λ_{sk}) capture factors that are specific to a vehicle segment and quality metric. For instance, vehicles in the luxury segment commonly adopt advanced technologies (such as lane change assist and blind spot assist that enhance vehicle safety) that other segments rarely use. Model by year fixed effects (λ_{it}) absorb time varying changes that affect the overall model quality. $\widetilde{\text{Score}}_{ikt}$ captures model i's relative strength in a quality dimension k in year t, after partialling out dimension-year, segment-dimension, and model-year fixed effects.

In the next step, we construct all possible follower-leader pairs using models in the same year, where a leader is a JV model (e.g., BMW-Brilliance X3) and a follower is a model by an affiliated (e.g., Brilliance H230) or non-affiliated domestic automaker (e.g. BYD F3). We regress follower i's relative quality strength on that of leader j:

$$\widetilde{\text{DMScore}}_{ikt} = \alpha + \beta_0 \widetilde{\text{JVScore}}_{jkt} + \widetilde{\text{JVScore}}_{jkt} \times \text{Z}_{ij}\beta_1 + \epsilon_{ijkt} \tag{2}$$

where $\widetilde{\text{DMScore}}_{ikt}$ and $\widetilde{\text{JVscore}}_{jkt}$ are residualized scores for model pair $\{i, j\}$ in year t and metric k. Z_{ij} is a vector of pair attributes, such as whether the pair is produced by affiliated automakers (i.e., a domestic automaker and its affiliated JVs), which is our primary focus. We also examine pairs that belong to the same vehicle segment. This vector of pair attributes allows us to investigate the scope and channel of knowledge spillover.

The identification of β_0 and β_1 relies on two sources of variation: the cross-sectional association in relative strength (or weakness) and contemporaneous co-movement in quality (net of overall time trend). Our identification strategy is best illustrated using a specific example. Figure 4 shows engine quality and fuel efficiency of four models, two by JVs (BMW-Brilliance and Nissan-Dongfeng) and two by the affiliated domestic automakers (Brilliance and Dongfeng). The JV model by BMW-Brilliance has a more reliable engine but is less fuel efficient than the model by Nissan-Dongfeng. The two domestic models that are produced by Brilliance and Dongfeng exhibit similar relative strength and weakness. We take this as evidence of knowledge spillover. Our empirical analysis below examines whether such patterns hold true systematically.

Our empirical framework represents a significant departure from the existing literature on knowledge spillover from FDI to domestic firms, which mainly relies on TFP variations at the industry level while controlling for standard panel fixed effects (e.g., Haddad and Harrison (1993); Aitken and Harrison (1999); Javorcik (2004); Keller and Yeaple (2009)). The key identification concern is that these fixed effects may be inadequate in controlling for other industry-time level shocks that affect both the entry of foreign firms and the performance of domestic firms, such as government policies targeting certain industries. By focusing on different dimensions of quality measures *within* a product-year, our analysis explores a much finer level of variation and allows us to control for *time-varying* unobservables at the firm and product level. At the same time, this rich set of controls soak out industry-wide quality improvement. Therefore, if spillover from JVs benefits both affiliated automakers and non-affiliated automakers by the same magnitude, the estimate of β_1 will not capture this – rightly so – as ownership affiliation is not required for this to happen.[21]

Finally, the two-step procedure in Equations (1) and (2) has advantages over the standard one-step estimation with all the fixed effects. First, this allows us to control for the time-varying average quality for the domestic models and JV models separately. The standard one-step estimation can only control for the average quality for the followers. Second, as shown by Lee and Lemieux (2010), partialling out fixed effects first can increase the efficiency of key parameter estimates β_1 while maintaining consistency under very mild conditions. We present our main results using the two-step estimation procedure and perform robustness checks using the standard fixed-effect model in Section 4.1.

3.2 Evidence of Relative Strength

A premise for our empirical analysis is that models produced by different JVs have differential quality strengths that domestic firms learn from. Figure 5 illustrates graphically JV models' quality variation along three performance dimensions: driving dynamics, engine, and fuel efficiency. It is evident that firms have different comparative advantages. For example, models by VW-FAW and Hyundai-BAIC enjoy better driving dynamics. VW-FAW and BMW-Brilliance have more powerful and reliable engines. Nissan-Dongfeng excels at fuel efficiency. These patterns are consistent with the common perception that German brands have prime engine performance while Japanese brands are more fuel efficient.

To quantify the extent of similarity in quality strength among models produced by the same JV firm, we estimate Equations (1) and (2) using JV pairs. We randomly assign half of all JV models as leaders and the rest as followers. Then we take all models in a year to form an exhaustive list of pairs and compute the residualized scores for each JV model and regress follower scores on leader scores. This exercise also serves as a proof of concept for our spillover analysis below. If the framework is capable of identifying relative strength among products within the same JV firm, we can use it to examine similarity in relative quality strength between JV models and domestics models.

As shown in Table 2, the coefficient estimate on the interaction term between LeaderScore and SameFirm, β_1, is positive and statistically significant.[22] It is also economically meaningful. When we

[21] One may be concerned that part of the industry-wide quality improvement is due to the *quid pro quo* policy - the non-affiliated domestic firms may have benefited more from the presence of the JVs compared to a world with unrestricted foreign entry. We discuss this in Section 6 and perform additional analysis to shed light on this counterfactual.

[22] As the follower and leaders are randomly assigned, the coefficient estimate of β_0 has no causal interpretation and is purely the correlation in quality between a random pair of models.

control for firm fixed effects, as well as dimension-year and dimension-segment fixed effects, a reduction of 10 defects in a JV model is associated with a reduction of 1.4 defects in the same quality dimension among other models by the same firm. The coefficient is stable across different columns of Table 2, with different combinations of firm, firm-year, model, and model-year fixed effects. Such within-firm cross-model correlation corroborates the patterns in Figure 5. Firms indeed specialize in different quality dimensions, which enables our analysis below examining spillover from JVs to domestic firms.

4 Results on Knowledge Spillover

4.1 Main Results

Our unit of observation is a domestic-JV pair by quality metric by year, with a total of 591,280 observations. There are 12,634 distinct domestic-JV pairs and 639 belong to affiliated pairs. We have nineteen quality metrics: nine IQS quality dimensions and ten APEAL performance dimensions.

Table 3 presents estimation results for Equation 2. While our main specification controls for product by year fixed effects λ_{it}, we also report less demanding specifications in Columns (1) to (5) with fixed effects for firm, firm-year, or firm-year and model. These alternative specifications absorb endogenous selection at the firm or model level: for example, the average quality of affiliated domestic firms might be systematically higher than that of non-affiliated automakers, or models introduced by affiliated-firms are different from those by non-affiliated automakers.

Column (1) partials out firm, dimension-year and dimension-segment FEs. The null coefficient on the JVScore itself should not be surprising, given that a domestic model's leader is defined to be all JV models, regardless of whether there is an ownership affiliation. SameGroup dummy flags follower-leader pairs that come from JVs (e.g., BMW-Brilliance) and their affiliated domestic partners (Brilliance). The interaction term between JVScore and SameGroup dummy is positive and statistically significant, suggesting a positive association in the relative quality strength between two models within the same group. The coefficient estimate (0.03) is much smaller than that for pairs of the same JV firm (0.14) in Table 2. This is intuitive in that the association between a JV model and a model from an affiliated domestic firm is naturally weaker than that between two models from the same firm.

Column (2) adds interaction terms to flag pairs that belong to the same vehicle segment (SameSegment) and ownership group (SameGroup). Once we control for the interaction between SameGroup and SameSegment, the SameGroup coefficient becomes small and insignificant. This indicates that spillover occurs primarily among products in the same segment (e.g., sedan or SUV). Therefore, for the remaining empirical analysis, we primarily focus on follower-leader pairs belonging to the same segment. In Columns (3) to (6), we gradually add more FEs to absorb firm-year, model, and model-year variations. The results remain robust. Taking the most demanding specification in Column (6), our main specification, the coefficient estimate of the interaction between SameGroup and SameSegment is economically significant: 13.8% of the quality improvement observed in a JV model would be transmitted to the affiliated domestic models in the same segment. This is similar in magnitude to the estimated shared quality strength among models within the same JV firm but across different segments (Table 2).[23]

Robustness checks Our baseline regressions focus on contemporaneous changes in leader quality. Table B.4 analyzes the dynamic spillover effects based on leaders' past quality measures. As there is a proliferation of new models in our sample period, a large number of models are observed for only a short time span. For this exercise, we use a balanced subsample of JV and domestic models that were sold every year between 2009 and 2014. Column (1) repeats the baseline regression. Knowledge spillover is stronger for this subsample than all affiliated model-pairs: the key coefficient β_1 is 0.258 vs 0.138 in Column (6) of Table 3. These are older and more popular models that have longer exposure to their leaders. Columns (2) to (4) lag a leader's quality score by one, two, and three years. The coefficient of past leader score is remarkably persistent, even in the specification with a three-year lag. These results are consistent with a dynamic learning process: domestic firms observe production techniques of affiliated JVs models, then gradually learn and incorporate them into their own production process.

Our regressions so far are based on residualized quality measures after partialling out the model-year, score-segment, and score-year fixed effects, separately for leaders and followers. Table B.5 reports the results of running fixed effect regressions instead of taking residuals first, using the same fixed effect combinations as in Table 3. Mathematically, these regressions are not the same as the two-step procedure in Equations (1) and (2), but the estimates are similar, and all of them suggest that knowledge spillovers occur in the same segment and same group.

Standard errors in Table 3 are two-way clustered by i's firm and quality dimension as well as j's firm and quality dimension. This allows for cross-sectional and temporal correlation of a given quality dimension (e.g., engine) across models in the same firm. Table B.6 reports the standard errors clustered in six different levels, including clustering by the leading firm and following firm, by the firm pair, or by firm-year. Our results are robust to all of these different levels of clustering.

4.2 Alternative Explanations

So far we have interpreted the finding that domestic models mimic quality strength of their affiliated JV models as evidence of knowledge spillover. Next we examine several alternative interpretations, including endogenous JV formation, overlapping customer bases, and market transactions of technologies.

[23]Most JVs have only one model in each vehicle segment. Therefore, we cannot examine the interaction between SameFirm and SameSegment in Table 2.

Endogenous JV formation One might be concerned that the ownership network – the set of domestic firms that form a joint venture with foreign auto producers – is not random. For example, domestic automakers may seek foreign partners who have strength in different quality dimensions in order to overcome their weakness. The initial negative correlation in quality strength between the follower and the leader could bias the coefficient estimates downward, masking evidence of knowledge spillover. On the other hand, if foreign firms choose to partner with domestic firms with similar quality strength, it would bias the estimates upward.

To address this issue, we first exploit an important institutional feature. Most major JVs in the Chinese auto industry were formed between the 1980s and the early 2000s, a period when domestic automakers had limited technological capacity and strength in any given quality dimension. Most of the domestic automakers started as producers of agricultural machinery (such as tractors) or heavy-duty trucks, and had very limited technological know-how in passenger vehicle production. The domestic automakers did not start to develop their own indigenous brands until the mid 2000s. Therefore, for these early JVs, it would have been very difficult, if not impossible, for the foreign automakers to predict the strength/weakness of the potential Chinese partners decades later, let alone to base their partnership decisions on those predictions. Table 4 Column (2) repeats our baseline specification by restricting the sample to JVs that were formed prior to 2000, which are unlikely driven by strategic partnership considerations based on relative quality strength due to reasons discussed above. Compared to the baseline estimate in Column (1), if anything, spillover appears to be stronger from these earlier JVs. The results alleviate the concerns of endogenous ownership formation.

To further control for any initial (either negative or positive) correlation in quality strength between follower and leader pairs, we partial out *model by quality dimension* fixed effects in Column (3). This specification absorbs any time-invariant quality strength of the followers and leaders in each quality dimension. Thus, the identification purely relies on *temporal co-movement* in quality measures between the followers and leaders, independent of any initial selection effect. Our results of positive spillover from JVs to their affiliated domestic partners continue to hold under this demanding specification.

Overlapping customer bases The second identification threat is that models by affiliated automakers are designed to appeal to the same group of consumers, leading to a positive correlation in product quality. We use household choices reported in the vehicle ownership survey to evaluate whether JVs and domestic automakers have overlapping customer bases. We estimate the following equation:

$$\begin{aligned} Log(\text{TopTwoChoices}_{ijt}+1) &= \alpha+\beta_1\text{SameGroup}_{ij}+\beta_2\text{SameGroup}_{ij}\times\text{SameSegment}_{ij} \\ &+ X_{ijt}\gamma+\lambda_t+\varepsilon_{ijt} \end{aligned}$$

The sample consists of all pairwise combinations of models in the same year. $\text{TopTwoChoices}_{ijt}$ counts the number of times model pair $\{i, j\}$ is listed as the top two choices by some household. A larger number suggests that the model pair is considered by more households as close substitutes and is evidence that both models compete for similar customers. The key regressors are SameGroup dummy and its interaction with SameSegment dummy as defined in section 4.1. Controls include for same segment, same ownership type, same firm, as well as differences in prices, car sizes, and engine powers.

There is no evidence that affiliated model pairs are more likely to attract similar customers than a random pair of JV and domestic models, ceteris paribus (Table 5). If anything, the estimates suggest that an affiliated model pair in the same segment are slightly less likely to be considered top two choices. This is not surprising given that JV models are considerably more expensive than indigenous models and target wealthier households.

One might be concerned that even if JV and domestic models target different customer groups, consumer perception of quality strength, as reflected by APEAL scores, might be affected by the ownership affiliation. For example, consumers may perceive that Brilliance produces models with strong engine performance because it has a joint venture with BMW (BMW-Brilliance). To address this concern, we examine IQS and APEAL scores separately. While APEAL measures consumer attitude and perception, the IQS survey is designed to be objective and reports the number of defects. Table 6 shows that the estimate for knowledge spillover is remarkably stable whether we use IQS, APEAL, or both. Together, these results indicate that association in relative strength across different quality dimensions is unlikely to be driven by demand-side confounding factors.

Direct technology transfer A common challenge in the broad literature that studies the impact of FDI on knowledge spillover is that data on market transactions of technology transfer are rarely observed (Keller, 2004). One could argue that the identified spillover might be driven by unobserved market transactions.

To address this concern, we obtain data on all patent transfers from the National Intellectual Property Administration (i.e., the Chinese Patent Office). During the period between 2009 and 2016, there were 116,440 cases of patent licensing and 140,499 cases of patent assignment nationwide, of which 899 and 2,744 happened in the auto industry. Among the 899 cases of patent licensing, 880 were between a parent company and a subsidiary company, or between two subsidiary companies under the same parent company. However, only four cases originated from a foreign automaker and none originated from a JV. Among the 2,744 cases of patent assignment among automakers, none of them originated from a JV.

The lack of direct patent transfer from JVs to domestic firms is consistent with the findings in Holmes, McGrattan, and Prescott (2015), which shows that JVs file a small number of patent applications in China compared to either Chinese domestic firms or foreign multinationals, highlighting the intellectual property challenge faced by JVs. During 2005 to 2010, JVs only filed 142 patents to the Chinese Patent Office compared to 14,500 patents filed by foreign automakers. Affiliated domestic automakers filed 936 patents and non-affiliated automakers filed 3,277.

In sum, we have shown that domestic models share similar quality strengths with affiliated JV models, and this pattern is not driven by endogenous JV formation, overlapping customer bases or direct technology transfers.[24] The results support the interpretation of knowledge spillover via the ownership network. Next, we investigate potential underlying mechanisms of such knowledge spillover.

5 Mechanisms of Knowledge Spillover

The vehicle production process includes interrelated stages from product planning (e.g., market analysis), design and engineering (e.g., chassis, power train, exterior and interior), sourcing of parts and components, testing, and assembly. The whole process involves complex interactions of technologies, equipment, and workers. Knowledge spillover could occur during all stages of the production process and through many different channels, including deliberate communication among the partners, flow of know-how through shared parts suppliers, knowledge exchange embodied in workers changing jobs, etc. In this section, we examine two potential mechanisms, namely worker flows and supplier network. We focus on pairs of domestic and JV models in the same vehicle segment, for which we have observed the strongest spillover effect (Table 3). The main takeaways are robust when we expand the sample to include all pairs.[25]

5.1 Worker Flows

Flow of workers, as carriers of knowledge, can lead to knowledge spillover across firms. Before foreign automakers entered China, passenger vehicle production was nearly non-existent and the labor force in the auto industry was small with few experienced technicians or executives. The JVs provided a training ground for both engineering skills and managerial knowhow. As workers move from JVs to domestic automakers, they bring valuable knowledge with them. Many high-level managers and skilled workers in domestic automakers have gained valuable experiences in JVs.

Using job switches that are compiled from user profiles on LinkedIn (China), we first document that workers are considerably more likely to move from JVs to affiliated SOEs.[26] Among all workers who switched jobs from a JV to a domestic firm, 27.2% moved to the JV's affiliated domestic firm. This

[24] There could be other time-varying unobservables that push the JVs and domestic automakers to specialize in similar quality dimensions, such as joint input purchases or marketing activities. Our discussion with industry experts suggests that these joint activities are uncommon. JVs and affiliated domestic automakers are independent business entities.

[25] The results are available upon request.

[26] Among all job switchers, 52.6% moved from a JV to another JV, 47.4% moved from a JV to a domestic automaker, 36.8% from a domestic automaker to a JV and 63.2% moved for a domestic automaker to another domestic automaker.

fraction would have been 9.3% if worker movements were random.[27]

We then examine the extent to which worker flow mediates knowledge spillover through ownership affiliation. We measure the intensity of worker flow using the number of job switchers between each pair of JV and domestic firms and standardize it across all observations. Then we interact worker flow with the same-group dummy. Table 7 summarizes the results. Column (1) shows that spillover is on average 14.3% between affiliated pairs. Column (2) shows that spillover is 6.3% when worker flow is at the national average and increases by 3% for each standard-deviation increase in the volume of worker flow. The estimates suggest that worker flow explains 58% of knowledge spillover from JVs to affiliated automakers.[28]

Some underlying factors, such as closer connections between firms, could result in both a larger worker flow and more knowledge spillover. Column (3) additionally controls for the reverse worker flow from the domestic firm to the JV, which is a proxy for business connections between the two firms. We find similar effects for JV-to-domestic worker flows, and no appreciable effect for domestic-to-JV flows. The asymmetric results are consistent with anecdotal evidence that domestic firms benefit from recruiting technicians with working experience at JVs, especially in key production areas with technology bottlenecks (Liu, 2019). Column (4) examines whether the effect is larger for the flow of skilled workers. To do that, we limit the sample to observations with positive JV-to-domestic flows and compute the share of technicians, classified based on job titles.[29] Consistent with the previous literature (e.g., Poole (2013)), we find that knowledge spillover is positively correlated with the movement of technicians. The coefficient is large and positive, though not precisely estimated.

While variations among worker flows across firms are not exogenous, these patterns provide suggestive evidence that worker flows play an important role in mediating knowledge spillover. These findings are consistent with the existing literature, which has documented that the benefit to a receiving firm is more pronounced when workers move from more productive firms to less productive firms, rather than the other way around, and that the flow of skilled workers brings greater knowledge transmission compared to non-skilled workers (Poole, 2013; Stoyanov and Zubanov, 2012b). Our finding also corroborates a popular view among industry experts that the presence and growth of JVs have trained a large number of technicians for the Chinese auto industry, generating an important positive externality to domestic firms.

[27] For this, we hold the number of workers moving from and to each firm fixed, and randomize who moves where. For example, if 30% of worker outflows come from firm A and 20% of worker inflows go into firm B, the fraction of workers moving from A to B would be 6% if the flow is random.

[28] An affiliated pair has an average worker flow z-score of 2.78. Additional worker flow from JVs to affiliated automakers contributes $2.78 \times 0.03 = 0.083$, or 58% of knowledge spillover (baseline is 0.143).

[29] We classify workers into tech-relevant and non-tech-relevant workers using the occupation classification by LinkedIn. Tech-relevant workers include designers, mechanical engineers, software engineers, procurement, quality control, and R&D. The rest are considered non-tech-relevant workers. Examples include operations, sales, media and outreach.

5.2 Supplier Network

Supply network can serve as another important conduit for knowledge spillover. This is especially true for the automobile industry, where quality of parts and components is a key determinant of a vehicle's performance. The presence of JVs have been argued to have helped and incentivized domestic part suppliers to improve their product quality, which benefited domestic automakers.[30] JVs' sourcing decisions may also provide valuable information to domestic partners and help the latter identify reliable and high-quality suppliers. Here, we examine the importance of the shared supplier spillover.

Our data affirm that ownership linkages have a sizable impact on supplier overlap. Affiliated model pairs share on average 12 common suppliers, compared to an average of 5.4 common suppliers between non-affiliated pairs.[31] We examine to the extent to which the shared quality strength between affiliated pairs could be driven by common part suppliers. For each model pair, we compute the Szymkiewicz-Simpson overlap ratio, which equals to the number of common suppliers divided by the smaller number of suppliers among the two firms. Then we standardize the overlap ratio across all observations and interact the standardized overlap ratio with the same-group dummy.[32] Table 8 reports results. A larger supplier overlap is indeed associated with stronger knowledge spillover. Estimates from Columns (1) and (2) imply that supplier overlap explains 32% of the knowledge spillover via ownership affiliation.[33]

The importance of shared supplier spillover echos findings from the existing literature. For example, using variation in supplier network generated by a trade policy shock in Bangladesh's garment industry, Kee (2015) finds that shared supplier network explains about 1/3 of the productivity spillover from FDIs to domestic firms. We obtain a similar estimate despite differences in context and methodology.

6 Policy Implications

Finally, we turn to the policy counterfactual of what will happen to domestic firms' quality if *quid pro quo* is lifted. Like many industrial policies, the *quid pro quo* policy was introduced nationwide. The counterfactual of 100% foreign ownership is never observed in this empirical setting. Our identification strategy therefore exploits a different type of variation, leveraging rich within-product information across different quality dimensions. While our rich set of controls mitigates the concerns of endogenous selection, it does leave open the question of whether we can extrapolate our findings to shed light on

[30] China's 1994 Auto Policy, which was lifted after China's WTO entry in 2001, required all JVs to localize at least 40% of their parts and components. This has led to the development of the upstream industry. For example, the localization rate for FAW-VW Jetta was only 24 percent in 1994 and reached 84 percent by 2000 (Gallagher, 2003).

[31] Marklines focuses on first-tier suppliers. On average, a JV model has 64 suppliers, while a domestic model has 32 distinct suppliers.

[32] We drop 3% of pairs where at least one model has fewer than five distinct suppliers to reduce measurement error in the overlap ratio. Results are similar with the full sample.

[33] An affiliated pair has an average worker flow z-score of 1.10. Additional worker flow contributes $1.1 \times 0.039 = 0.043$, or 31% of knowledge spillover (baseline is 0.138).

what would happen in the absence of *quid pro quo*.

To address the policy question, we present a set of additional reduced form evidence in this section, exploring the partial overlap between ownership and geographical networks as well as variations in ownership structure in the upstream industry. We end this section with a quantification exercise where we lift the *quid pro quo* policy in 2009 and simulate counterfactual quality evolution of domestic models.

Is *Quid Pro Quo* a prerequisite for knowledge spillover? Our first analysis examines whether ownership affiliation stipulated by the *quid pro quo* policy is a prerequisite for knowledge spillover. To that end, we ask whether unaffiliated automakers, who are not the direct beneficiaries of this policy, also benefit from the JVs. Exploring the partial overlap between the ownership network and geographical network as shown in Figure B.4, we construct a dummy for two models located in the same city and interact the ownership dummies (SameGroup and DiffGroup) with the location dummies (SameCity and DiffCity). Column (1) of Table 9 replicates Column (6) of Table 3, focusing on follower-leader pairs in the same vehicle segment. Column (2) presents the full interaction between ownership and geography dummies. While the spillover between affiliated pairs in the same city is the strongest, there remains substantial knowledge spillover from JVs to non-affiliated domestic firms located in the same city. The estimated coefficient is 0.144, positive and statistically significant at 10 percent level. This provides evidence that while the ownership affiliation as required by *quid pro quo* facilitates learning, it is not a prerequisite for knowledge spillover.

Are affiliated domestic automakers necessary for knowledge spillover? A skeptical view of the findings above is that spillover to non-affiliated automakers could only happen with some form of *quid pro quo* in place, and that affiliated domestic partners are crucial conduits for knowledge to flow from foreign firms to domestic firms. To shed light on this, we exploit the fact that there are cities that host non-affiliated domestic firms together with JVs but without the presence of affiliated domestic automakers (see Figure B.4).[34] If the presence of an affiliated domestic firm is crucial in mediating knowledge spillover to non-affiliated domestic firms, we would expect the latter to benefit less from a JV in the absence of the former. Results are reported in Table 10. The sample consists of model pairs between non-affiliated domestic firms and JVs. The omitted group is non-affiliated domestic-JV pairs in different cities. The two key regressors are whether the model pair is located in cities with or without any affiliated domestic plant. If anything, the spillover from JVs to non-affiliated domestic firms in the same city is larger when there are no affiliated domestic firms, with a p-value of 0.016 for the equality of these two coefficients. This suggests that the presence of affiliated automakers is not a necessary

[34] One example of a city that hosts only non-affiliated plants and JV plants (i.e. the blue-purple circles in Figure B.4) is Chengdu. It has a plant by Geely (a private firm), plants by both Toyota-FAW and VW-FAW (JVs), but no plant by FAW or any other affiliated domestic firm.

conduit for knowledge spillover, which could happen via channels other than ownership affiliation.

Evidence from the auto parts industry While the downstream auto assembly industry is subject to *quid pro quo*, the upstream parts and components industry features a dynamic environment with both JVs and wholly foreign-owned firms and considerable variation in ownership composition across cities (as shown in Figure B.5).[35] Our third analysis further leverages the variation in ownership type in the upstream industry to examine whether wholly foreign-owned FDIs benefit domestic firms significantly less in terms of knowledge spillover compared to JVs.

We begin by constructing quality measures for the upstream suppliers in the following steps. First, we map the micro-level IQS scores (covering 227 components and functionalities for each model) to vehicle parts and components categories. This delivers a quality measure for each part category of each model in a given year. After that, using the supplier information in Markline, we construct a quality measure for each supplier i in part category k as the average of IQS scores over all models that source part k from supplier i, weighted by each model's sales.

We have compiled quality information for 1020 out of suppliers in MarkLine and non-missing ownership information for 660 of them. Among these firms, 347 are domestic, 127 are joint ventures, and 206 are wholly foreign-owned. For each supplier, we observe quality measures over 1 to 13 part categories (of 25 categories in total), with an average of 3 part categories per supplier.

Next, following our main empirical strategy, we form follower-leader pairs using all domestic and JV/foreign suppliers in the same year (from 2009 to 2014) for the same part category, and replicate our analysis as outlined in Equations (1) and (2) for the upstream industry. We are interested in examining whether spillover to domestic firms is smaller from wholly foreign-owned firms than from JVs.

Table 11 shows the regression results. The results are qualitatively robust across columns with different combinations of fixed effects.[36] While domestic firms appear to benefit more from foreign firms located in the same city (Columns (1) and (3)), whether the latter is a wholly foreign-owned entity or a joint venture does not appear to matter (Columns (2) and (4)). We do not find evidence that knowledge spillover from wholly foreign-owned FDIs is significantly less than that from joint ventures.

In general, the existing literature has documented mixed evidence on whether domestic firms benefit more from JVs compared to wholly foreign-owned firms. For example, Blomström and Sjöholm (1999) show that the degree of foreign ownership at the industry level does not affect the degree of spillover

[35] Figure B.5 shows the distribution of ownership type by the number of firms and sales revenue across cities using the annual survey of manufacturing firms conducted by the National Bureau of Statistics (NBS). There are two approaches in the literature to identify a firm's ownership type, either using the registration type (Yu, 2015) or the shareholder information based on registered capital (Brandt, Van Biesebroeck, and Zhang, 2012; Hsieh and Song, 2015). Since our focus is on the distinction between joint venture and sole foreign ownership, we follow the second approach to define a firm's ownership type. Results are robust to the alternative definition.

[36] Due to the relatively small number of part categories per supplier (on average 3), we take out firm or firm-category instead of firm-year fixed effects. The latter gives us qualitatively similar findings. Results are available upon requests.

to domestic firms. On the other hand, using firm-level data from Lithuania and Romania, respectively, Javorcik (2004) and Javorcik and Spatareanu (2008) document spillover to upstream suppliers (vertical spillover) from joint ventures but not from wholly foreign-owned investment. Conceptually speaking, whether the spillover is stronger from JVs depends on the absorptive capacity of domestic firms, technology gaps between the two and the nature of competition. Our finding from the upstream parts and components sector is probably more relevant for the auto industry, given the similarity in technology progress and the absorptive capacity of domestic firms.

Effects of lifting *Quid Pro Quo* in 2009 We end our policy discussions with a simple quantification exercise of what would have happened to the quality of domestic automakers if *quid pro quo* was lifted in 2010. Since our empirical identification is based on relative quality strength between followers and leaders, additional assumptions are needed to quantity the policy's impact on the *overall* quality levels of domestic models. We make the following assumptions. First, we take the linear specification in Equation (2) literally and assume that the size of spillover among the affiliated pairs is proportional to the quality gap between the two. Second, for followers with multiple leaders, we use the average predicted quality. Appendix A provides more details. It also illustrates how knowledge spillover of this nature translates into shared relative quality strength between leader and follower models, and that estimates based on relative quality strength (Equations (1) and (2)) capture the intensity of spillover.

We experiment with two different assumptions on the dynamics of knowledge spillover. The first scenario assumes that knowledge spillover and learning are proportional to the difference between current JV model quality and domestic model's quality in 2009.[37] The second scenario assumes that learning occurs cumulatively each year. The benefit affiliated domestic automakers receive in a particular year embodies all past learning with no depreciation, where learning in a given year is proportional to the quality difference in that year.[38] Which assumption is more appropriate depends on the nature of learning (the frequency of model redesigns, persistence of the acquired technical skills, etc.). We use the two scenarios to bound our predictions on the effects of *quid pro quo*.

Figure 6 shows results based on our baseline estimate in Table 3. We take 2009 as the baseline year and assume that the effect of the policy removal starts to take place in 2010. We use total IQS score as the quality measure of interest. The solid lines plot observed annual average IQS scores for JV, affiliated domestic models, and non-affiliated domestic models. The dashed line plots the predicted quality of affiliated domestic models in the absence of *quid pro quo*. In the first scenario, lifting *quid pro quo* in 2009 would reduce average domestic quality in 2014 by 9% (around 12 more defects per model) for affiliated models, and 5.7% for all domestic models. Without *quid pro quo*, the affiliated

[37] For this exercise we use a subsample of domestic models that were released by 2009.

[38] One limitation of the cumulative learning assumption is that as time goes by, knowledge spillover from JVs could exceed 100% and explain all quality upgrading of domestic automakers.

domestic automakers, all of which are SOEs, would have been outperformed by their non-affiliated counterparts by 2014. With cumulative learning, the effect increases to a 23% reduction (around 33 more defects per model) for affiliated models and 16.5% for all domestic models. Note that in both exercises, any industry-wide knowledge spillover due to the presence of foreign automakers, absorbed by quality dimension by year fixed effects and quality dimension by segment fixed effects, is kept the same. Thus the key focus is on the role of *quid pro quo*'s stipulated ownership requirement.

Overall, our results show that while *quid pro quo* does facilitate domestic learning, it is not a prerequisite for knowledge spillover and does not account for the majority of the overall quality improvement experienced by domestic automakers. In light of the trade dispute between China and the US and the debate regarding the current relevance of the *quid pro quo* policy, our analysis suggests that removing the policy would not significantly hinder the process of domestic quality improvement.

7 Conclusion

This paper studies the effect of *quid pro quo*, the policy of technology transfer for market access, in facilitating knowledge spillover from developed countries to developing countries. Leveraging unique datasets on quality ratings, supplier networks, worker flow, and household surveys, we document consistent patterns of additional knowledge spillover from JVs to domestic automakers as a result of *quid pro quo* over the general spillover induced by the presence of foreign automakers. Consistent with the existing literature, worker flows and supplier network are the primary channels of such knowledge spillover. On the other hand, our analysis suggests that while ownership affiliation facilitates learning, it is not a necessary requirement for knowledge spillover and does not account for the majority of the quality upgrading experienced by domestic automakers during our study period.

Our findings imply that the recent pledge by the Chinese government to end *quid pro quo* in the automobile industry would not significantly hinder domestic quality upgrading. With a majority stake or even sole-ownership, foreign automakers could have stronger incentives to bring the most advanced technology to the Chinese market as they can better guard their know-how. How such incentives are shaped by global knowledge diffusion is an important open area for future empirical research.

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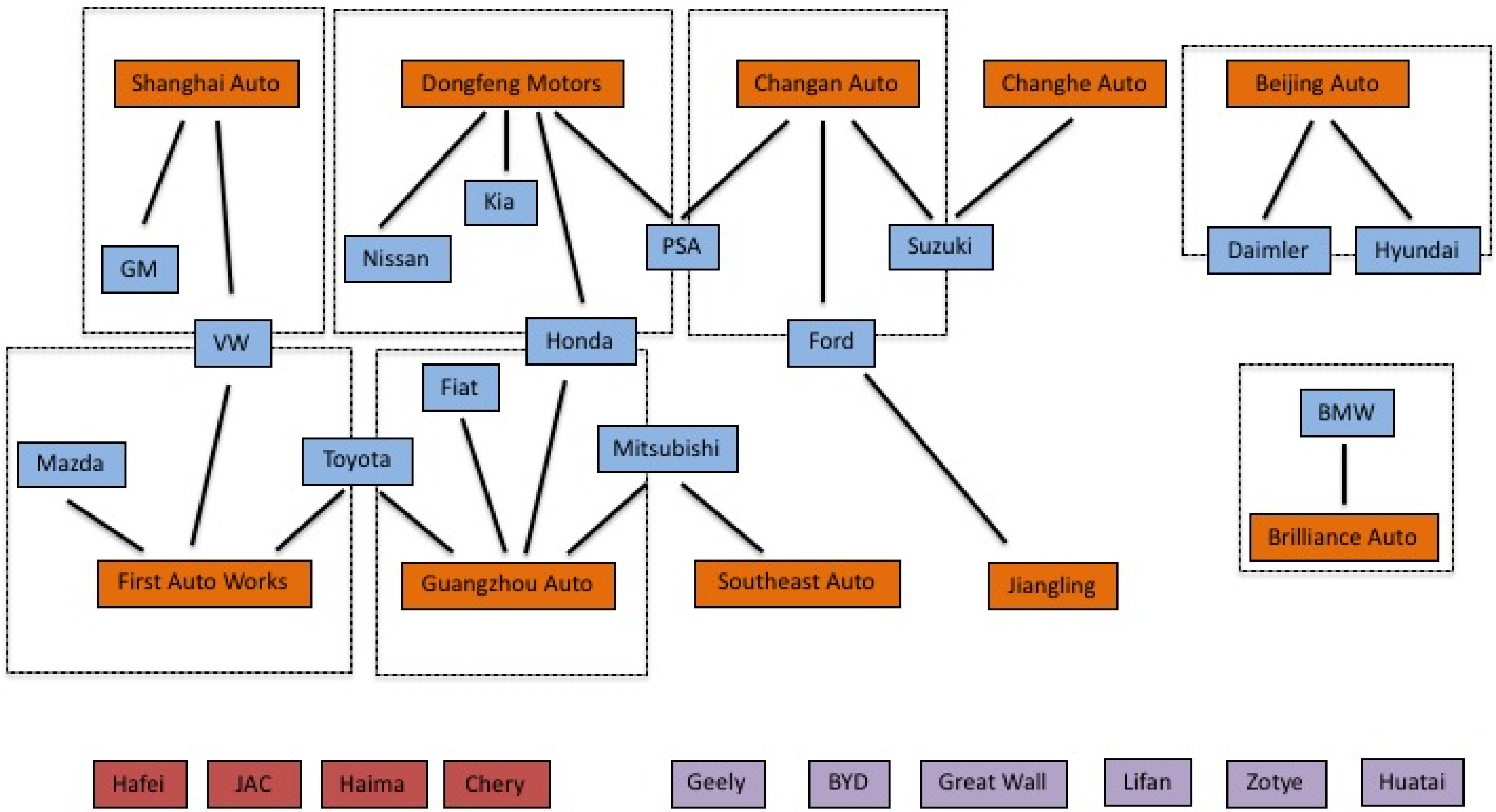
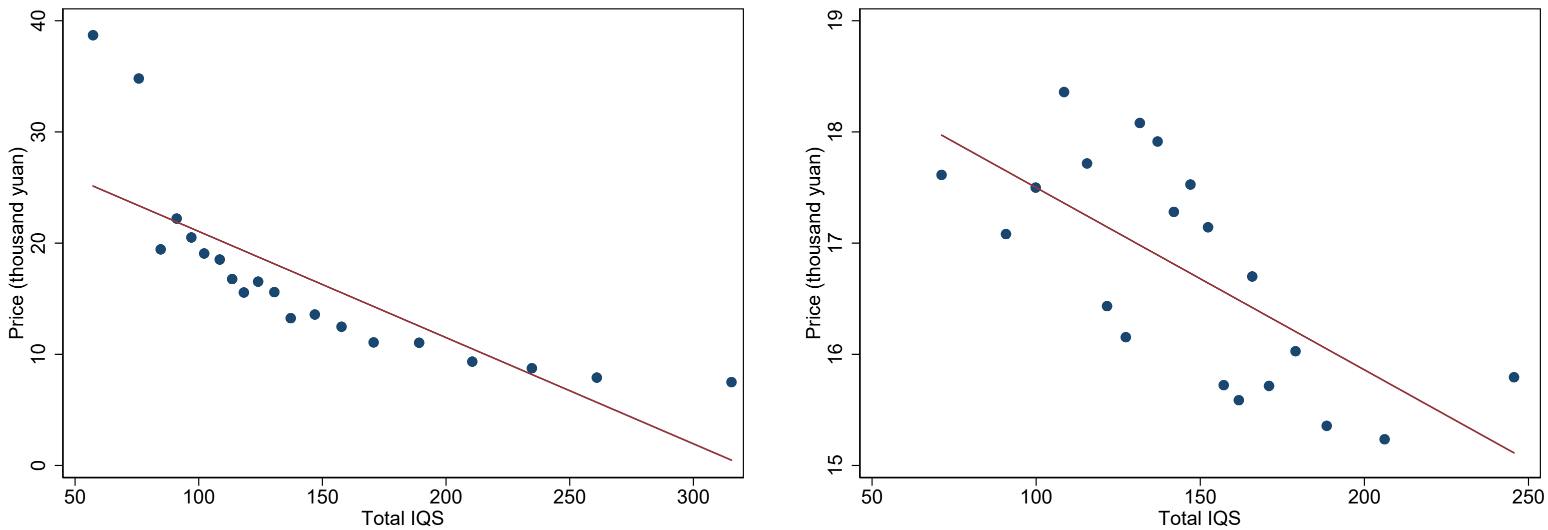
Figure 1: Joint Venture Network of the Chinese Auto Industry



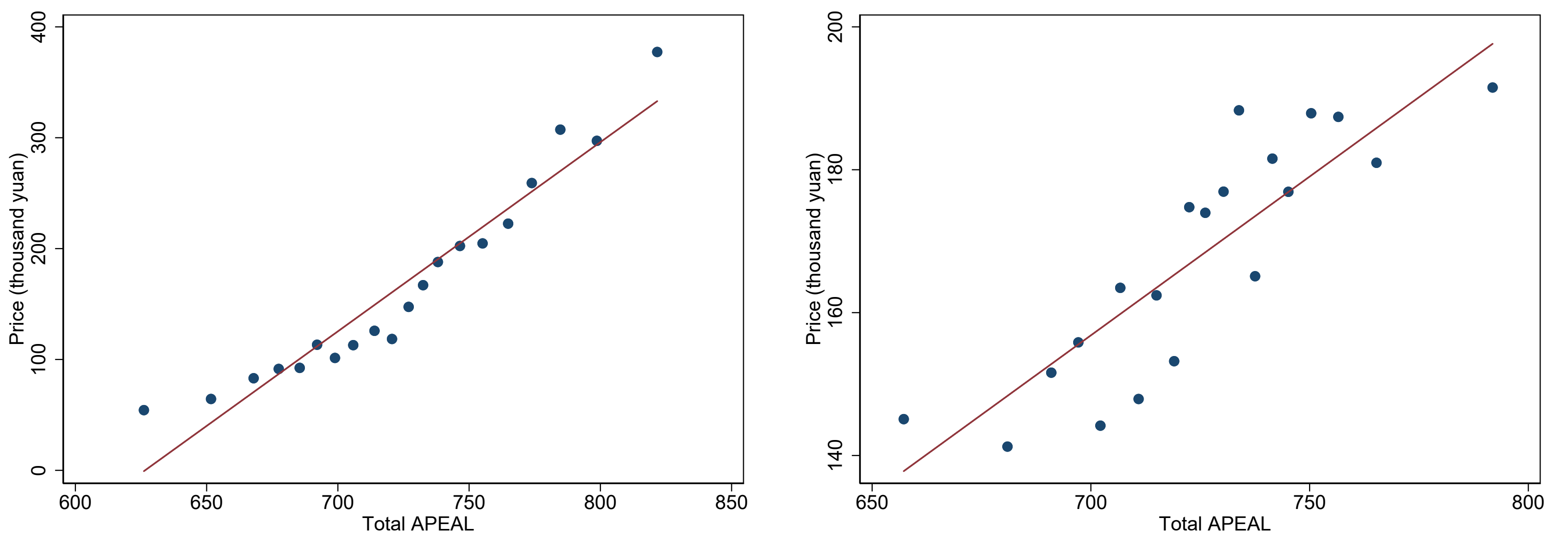
Notes: This figure is adapted from Figure 1 of Chen, Lawell, and Wang (2020). It describes the joint venture network of the Chinese auto market as of 2014. Orange boxes represent affiliated SOEs; blue boxes represent foreign partners in JVs; purple boxes represent private domestic automakers; red boxes represent non-affiliated SOEs. The dashed lines indicate groups of JVs that share the same affiliated domestic SOE.

Figure 2: Correlation between Vehicle Price and IQS Scores

Panel A. Vehicle Price vs. IQS

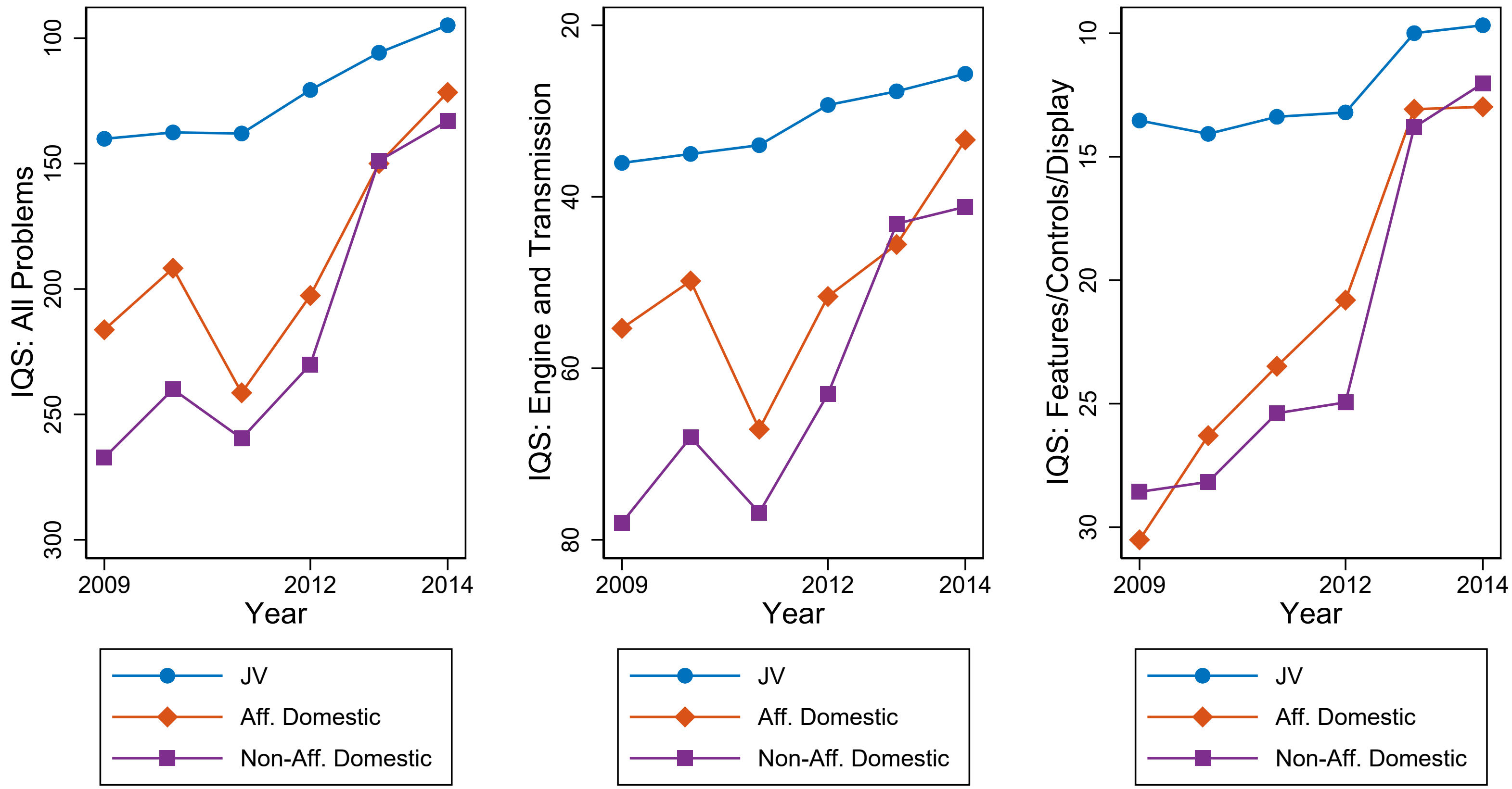


Panel B. Vehicle Price vs. APEAL



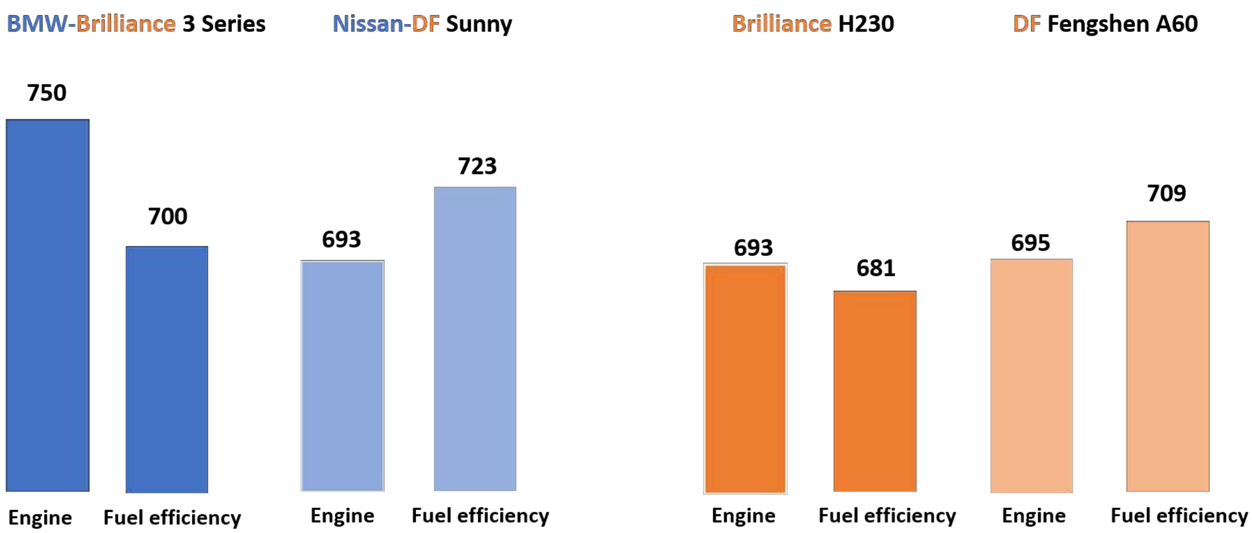
Notes: The figures are binned scatter plots between price and IQS (Panel A) and between price and APEAL (Panel B) The left figures control for vehicle size and horsepower/weight and the right figures further control for year fixed effects, segment fixed effects, and ownership type fixed effects. A lower IQS indicates less defects and hence better quality while a higher APEAL indicates better quality.

Figure 3: Descriptive Patterns of Quality Upgrading



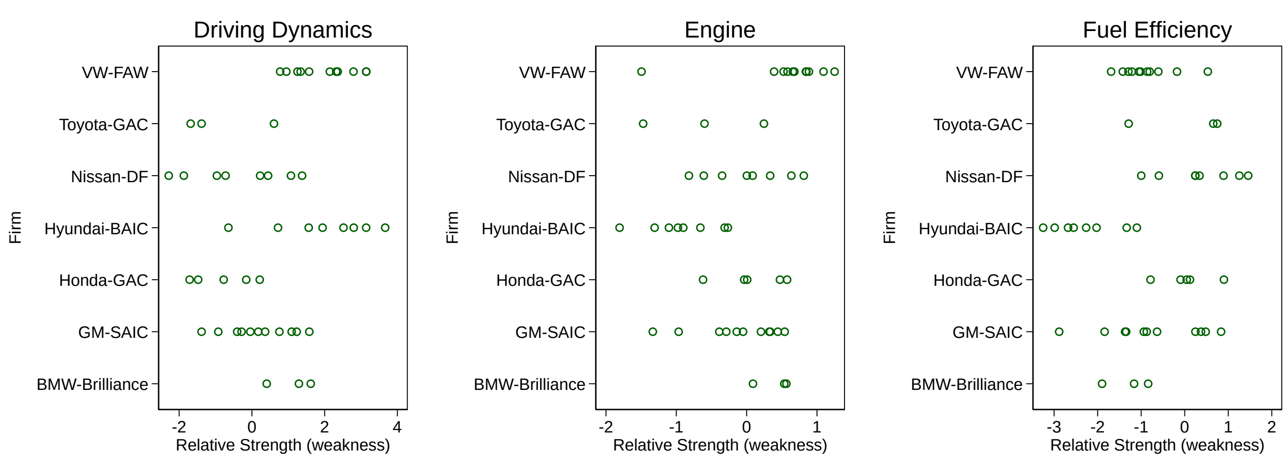
Notes: The vertical axis reports IQS scores, which is the number of problems experienced per 100 vehicles during the first 90 days of ownership across nine performance dimensions. Note that smaller numbers indicate higher quality (the vertical axis points downward), so that the blue line representing JV products lies at the top of the graph. The aggregate score (left figure) is the sum of scores over the nine dimensions. The middle and right figures show the time dynamics of two dimensions, namely engine and transmission and features/control/display.

Figure 4: Leader-Follower Pattern of Relative Quality Strength



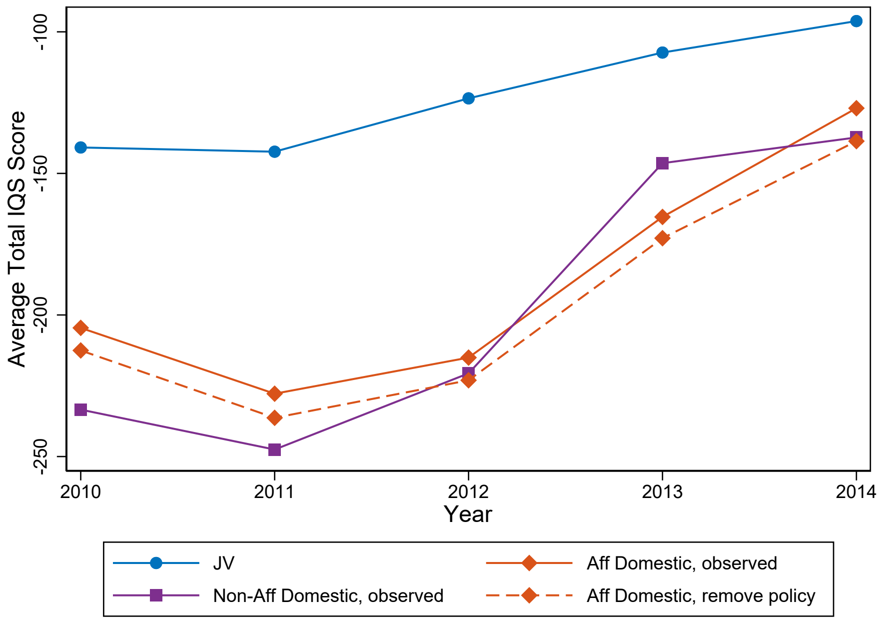
Notes: The bars show the quality scores for engine and fuel efficiency dimensions. The two models on the left are produced by JVs and those on the right are indigenous brands by affiliated domestic automakers.

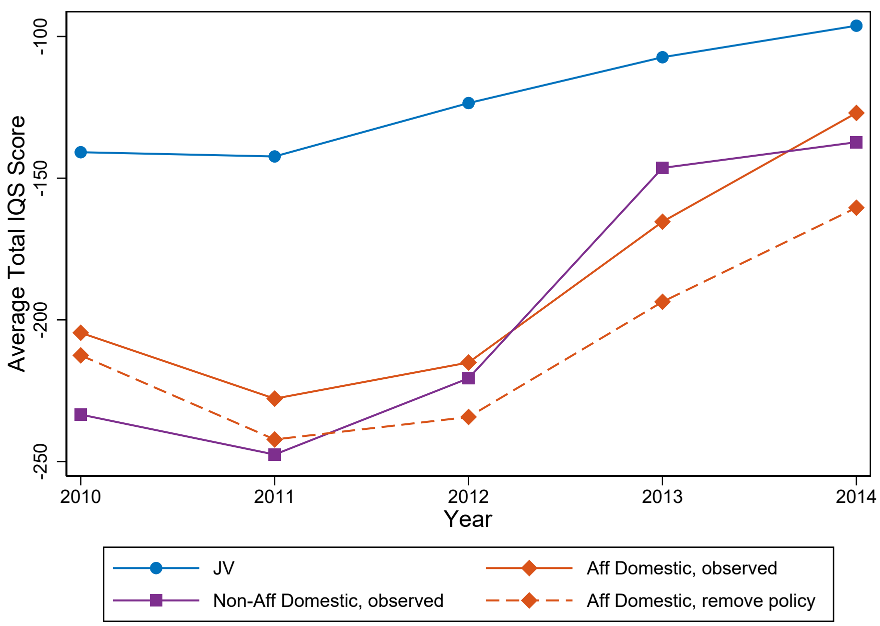
Figure 5: Differential Relative Quality Strength Among Leaders



Notes: This figure shows relative quality strength (after partialling out model-year and quality-dimension-segment fixed effects) across JVs along three vehicle performance dimensions measured in APEAL, namely driving dynamics, engine and fuel efficiency. Each circle represents a model produced by a given automaker. The sample includes vehicle models in all segments in 2014. The way of constructing the relative strength follows Equation 1 while using cross-sectional data.

Figure 6: Effects of Lifting *Quid Pro Quo* in 2009





Notes: The solid lines plot observed quality improvement in terms of the total IQS score for JV and domestic models. The dashed line shows the counterfactual quality dynamics of the domestic models if *quid pro quo* was lifted in 2009 (assuming the effect starts to takes place in 2010). The first panel assumes that knowledge spillover and learning are proportional to the difference between current JV model quality and domestic model's quality in 2009. The second panel assumes that learning occurs cumulatively each year. The benefit affiliated domestic automakers receive in a particular year embodies all past learning with no depreciation, where learning in a given year is proportional to the quality difference in that year. These two scenarios bound the effect of *quid pro quo*.

Table 1: Summary Statistics: IQS and APEAL Scores

Ownership	JV				Affiliated Domestic automakers				Non-affiliated Domestic automakers			
Year	2009		2014		2009		2014		2009		2014	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: IQS scores												
IQS 1: Audio/entertainment/navigation	5.44	3.67	5.17	2.80	7.93	6.99	4.20	3.27	6.62	3.17	4.31	2.84
IQS 2: The driving experience	29.39	14.35	20.31	6.98	40.78	16.99	25.82	7.73	51.64	14.44	27.42	6.04
IQS 3: Engine	22.63	10.25	18.56	7.59	38.59	16.28	21.53	6.42	43.84	10.47	25.72	6.15
IQS 4: Features/controls/displays	13.53	7.87	9.68	3.32	28.93	8.01	12.29	6.33	29.51	11.11	12.78	4.30
IQS 5: HVAC problems	16.39	7.23	8.91	4.37	25.82	8.82	11.46	6.12	27.73	9.33	11.89	5.24
IQS 6: Interior problems	13.39	6.52	7.73	3.55	21.47	10.93	9.69	3.40	19.74	5.54	10.48	4.81
IQS 7: Seat problems	5.21	3.67	4.56	2.51	6.04	3.76	5.15	2.36	8.26	3.82	5.35	2.82
IQS 8: Transmission	13.61	9.91	7.11	4.68	26.79	12.78	12.80	4.08	33.02	11.55	16.34	4.58
IQS 9: Exterior problems	23.19	13.72	12.82	5.84	39.24	15.26	20.51	8.15	50.91	19.26	19.37	6.56
IQS *total*	142.79	55.65	94.85	23.02	235.60	72.56	123.45	24.28	271.28	49.85	133.66	19.77
Panel B: APEAL scores												
APEAL 1: Audio, entertainment, and navigation	93.65	22.89	96.64	20.90	79.18	22.32	93.38	15.78	71.76	12.32	89.78	15.40
APEAL 2: Engine and transmission	40.68	1.92	40.21	1.32	37.58	2.73	38.60	0.79	36.57	1.16	38.34	0.83
APEAL 3: Exterior	58.99	2.49	57.51	1.88	56.49	3.81	55.61	1.14	55.03	1.64	55.18	0.91
APEAL 4: Heating, ventilation, and air conditioning	65.78	3.12	64.50	2.14	61.55	4.60	62.31	1.23	60.28	2.01	61.89	1.11
APEAL 5: Visibility and driving safety	71.80	5.96	72.12	3.89	66.38	7.79	69.52	3.43	63.10	4.60	69.15	2.99
APEAL 6: Driving dynamics	65.79	2.94	64.43	2.16	61.58	4.60	62.16	1.46	59.67	1.92	61.75	1.27
APEAL 7: Fuel economy	15.96	0.63	15.86	0.45	15.24	0.78	15.44	0.28	14.84	0.31	15.29	0.35
APEAL 8: Interior	114.12	5.64	112.40	3.56	108.18	7.27	108.76	2.03	105.28	3.07	108.13	1.79
APEAL 9: Seats	114.47	9.10	113.34	5.58	109.47	10.17	109.75	4.03	105.34	7.74	108.39	1.96
APEAL 10: Storage and space	89.39	5.94	87.59	4.71	84.23	8.08	82.84	4.65	80.72	6.20	82.62	4.59
APEAL *total*	730.62	52.14	724.60	39.74	679.88	65.26	698.38	24.07	652.60	30.44	690.52	22.23
Num of automakers	19		25		7		10		7		5	
Num of models	76		119		20		30		17		20	

Notes: The scores are at the model-by-year level, averaged over responses by around 100 car owners for each model-year. IQS scores measure the number of problem per 100 vehicle in the first three months of ownership in nine dimensions. APEAL scores are user satisfaction ratings in ten vehicle performance dimensions. Non-affiliated domestic automakers include all private Chinese automakers and non-affiliated SOEs that are not part of any JV.

Table 2: Relative Quality Strength among JVs

	(1)	(2)	(3)	(4)	(5)
LeaderScore	-0.008***	-0.006***	-0.008***	-0.007***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
× SameFirm	0.142***	0.109***	0.145***	0.122***	0.140***
	(0.020)	(0.016)	(0.021)	(0.017)	(0.020)
Firm FE	✓				
Firm-year FE		✓		✓	
Model FE			✓	✓	
Model-year FE					✓
Dimension-year FE	✓	✓	✓	✓	✓
Dimension-Segment FE	✓	✓	✓	✓	✓
Observations	292,334	292,334	292,334	292,334	292,334

Notes: We randomly assign each JV model to be either a follower or a leader (with 50% chance each), and match each leader and follower into pairs. The dependent variable is the quality score of a follower model. The unit of observation is a pair-year-quality dimension. Both leader and follower scores are residualized scores after taking out a set of fixed effects specified under each column. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 3: Knowledge Spillover from JVs to Domestic Firms

	(1)	(2)	(3)	(4)	(5)	(6)
JVScore	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
× SameGroup	0.026***	0.002	0.004	0.011	0.005	0.004
	(0.013)	(0.013)	(0.010)	(0.015)	(0.012)	(0.014)
× SameSeg		0.002	0.004	0.003	0.005***	0.002
		(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
× SameGroup × SameSeg		0.131***	0.107***	0.137***	0.113***	0.138***
		(0.018)	(0.019)	(0.020)	(0.017)	(0.021)
Observations	591,280	591,280	591,280	591,280	591,280	591,280
Partialling out:						
Firm FE	✓	✓				
Firm-year FE			✓		✓	
Model FE				✓	✓	
Model-year FE						✓
Dimension-year FE	✓	✓	✓	✓	✓	✓
Dimension-Segment FE	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We consider all pairs of models produced by JVs and domestic automakers. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after taking out various fixed effects. SameGroup is an indicator variable that equals to 1 if the two models belong to a pair of affiliated automakers. SameSeg is an indicator variable that equals to 1 if the two models belong to the same vehicle segment. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 4: Results on Endogenous JV Formation

	(1)	(2)	(3)
Founding Year	All	Before 2000	All
JVScore	-0.002	-0.002	-0.004***
	(0.004)	(0.004)	(0.002)
× SameGroup	0.004	-0.003	0.027***
	(0.014)	(0.021)	(0.007)
× SameSeg	0.002	-0.004	0.007
	(0.002)	(0.006)	(0.004)
× SameGroup × SameSeg	0.138***	0.210**	0.119***
	(0.021)	(0.030)	(0.017)
Observations	591,280	305,976	520,334
Partialling out:			
Model-Year FE	✓	✓	
Dimension-Year FE	✓	✓	✓
Dimension-Segment FE	✓	✓	
Dimension-Model FE			✓

Notes: The dependent variable is the quality score of a domestic model. We consider pairs of models produced by JVs and domestic automakers. The unit of observation is a pair-year-quality dimension. Column (1) replicates our main result (Column (6) of Table 3). Column (2) restrict to models produced by JVs that are formed prior to 2000. In Column (3), we construct residualized leader (JV) and follower (domestic) scores by partialling out dimension-year and dimension-model fixed effects. This specification only exploits temporal variation in leader's quality. SameGroup and SameSeg are defined as in Table 3 Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 5: Alternative Explanation: Overlapping Customer Base

Dep. variable: log(count of top two choices + 1)	(1)	(2)	(3)
SameGroup	-0.034***	-0.003	-0.009***
	(0.003)	(0.003)	(0.003)
SameSegment		0.082***	0.056***
		(0.007)	(0.007)
SameGroup × SameSegment		-0.021***	-0.017***
		(0.007)	(0.007)
SameOwnershipType		0.037***	0.025***
		(0.001)	(0.001)
SameOwnershipType × SameSegment		0.132***	0.130***
		(0.003)	(0.003)
SameFirm		0.051***	0.041***
		(0.003)	(0.003)
Observations	196,225	196,225	196,225
R-squared	0.015	0.075	0.087
Attributes Controls			✓

Note: The sample is constructed from the household car ownership survey. Each observation is a pair of models in a year. The dependent variable is the log number of times a pair is listed as the top two choices by some households in the survey data. Attributes controls include the difference in prices, car sizes, and engine powers. SameGroup and SameSeg are defined as in Table 3. SameOwnerShipType is takes value 1 if both are JV models or both are domestic models. In columns (2) and (3), the omitted group includes pairs that are not in the same segment and not produced by firms of the same ownership type, and not produced by affiliated automakers. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 6: Knowledge Spillover by IQS and APEAL Studies

	(1) All	(2) IQS	(3) APEAL
JVScore	-0.002	-0.001	-0.003
	(0.002)	(0.001)	(0.004)
× SameGroup	0.004	0.001	0.007
	(0.013)	(0.009)	(0.024)
× SameSeg	0.003	-0.000	0.006
	(0.002)	(0.003)	(0.004)
× SameGroup × SameSeg	0.138***	0.131***	0.144***
	(0.021)	(0.028)	(0.031)
Observations	591,280	280,080	311,200
Partialling out:			
Model-year FE	✓	✓	✓
Dimension-Year FE	✓	✓	✓
Dimension-Segment FE	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We consider all pairs of models produced by JVs and domestic automakers. The unit of observation is a pair-year-quality dimension. Column (1) replicates Column (2) of Table 3. Columns (2) and (3) split IQS and APEAL scores into different regression samples. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 7: Mechanism of Knowledge Spillover: Worker Flow

JVScore interacted with	(1)	(2)	(3)	(4)
× SameGroup	0.143***	0.063***	0.046***	0.055***
	(0.020)	(0.019)	(0.020)	(0.025)
× SameGroup × JVDomFlow		0.030***	0.026**	0.037***
		(0.008)	(0.010)	(0.011)
× SameGroup × DomJVFlow			0.012	
			(0.011)	
× SameGroup × JVDomFlow × HighTechShare				0.044
				(0.041)
Observations	115,159	115,159	115,159	69,331
Partialling out:				
Model-year FE	✓	✓	✓	✓
Dimension-Year FE	✓	✓	✓	✓
Dimension-Segment FE	✓	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model.The sample consists of domestic-JV pairs in the same vehicle segment where spillover is concentrated. The unit of observation is a pair-year-quality dimension. Both JV and domestic scores are residualized scores after taking out dimension-year, model-year and dimension-segment fixed effects. SameGroup is defined as in Table 3. JVDomFlow measures the number of workers who moved from the JV to the domestic automaker. Vice versa for DomJVFlow. We identify six "HighTech" occupations that are directly related to the IQS quality measures. Those are feature designers, mechanical engineers, software engineers, procurement manager, quality control, and R&D. HighTechShare is the fraction of worker flows that is in one of the six occupations. All pairs with 0 worker flow (and hence undefined HighTechShare) are dropped in column (4). Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 8: Mechanism of Knowledge Spillover: Supplier Network

JVScore interacted with	(1)	(2)
× SameGroup	0.138***	0.094***
	(0.020)	(0.022)
× SameGroup × SupplierOverlapRatio		0.039***
		(0.015)
Observations	111,796	111,796
Partialling out:		
Model-year FE	✓	✓
Dimension-Year FE	✓	✓
Dimension-Segment FE	✓	✓

Notes: The dependent variable is the quality score of a domestic model. The sample consists of domestic-JV pairs in the same vehicle segment where spillover is concentrated. The unit of observation is a pair-year-quality dimension. Both JV and domestic scores are residualized scores after taking out dimension-year, model-year and dimension-segment fixed effects. SameGroup is defined as in Table 3. SupplierOverlapRatio is defined as the number of common suppliers divided by the number of distinct suppliers reported by the pair (the smaller number of the two). Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 9: Knowledge Spillover: is *Quid Pro Quo* a prerequisite?

JVScore interacted with	(1)	(2)
× SameGroup	0.143***	
	(0.020)	
× DiffGroup	0.001	
	(0.005)	
× SameGroup × SameCity		0.188***
		(0.036)
× SameGroup × DiffCity		0.103***
		(0.023)
× DiffGroup × SameCity		0.144*
		(0.084)
× DiffGroup × DiffCity		-0.000
		(0.005)
Observations	115,159	115,159
Partialling out:		
Model-Year FE	✓	✓
Dimension-Year FE	✓	✓
Dimension-Segment FE	✓	✓

Notes: The dependent variable is the quality score of a domestic model. The sample consists of domestic-JV pairs in the same vehicle segment, which explains the smaller number of observations than Table 3. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after taking out dimension-year, model-year and dimension-segment fixed effects. Interaction terms are dummy variables indicating whether the two models belong to the same affiliated group of automakers or locate in the same city. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 10: Policy Counterfactual: Does Having Affiliated SOEs in a City Matter?

Sample: Pairs of models of non-affiliated domestic automakers and JVs	(1)
JVScore	-0.002***
	(0.000)
× SameCity × CityWithAffiliatedFirm	0.087**
	(0.044)
× SameCity × CityWithoutAffiliatedFirm	0.214***
	(0.040)
Observations	552,235
Partialling out:	
Model-Year FE	✓
Dimension-Year FE	✓
Dimension-Segment FE	✓

Notes: The dependent variable is the quality score of a domestic model. The sample in this exercise consists of all pairs of models produced by JVs and non-affiliated domestic automakers given that there are no pairs of JV-domestic models in the same segment and same city in cities where there is no affiliated automakers. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after taking out model-year, dimension-year and dimension-segment fixed effects. SameCity is an indicator variable that equals to 1 if the two models are produced in the same city. CityWithAffiliatedFirm and CityWithoutAffiliatedFirm are dummy variables indicating whether the city hosts an auto assembly plant by an affiliated domestic automaker. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table 11: Knowledge Spillover: Evidence from the Upstream Auto Parts Industry

	(1)	(2)	(3)	(4)
ScoreLeader	-0.006*	-0.006*	-0.008	-0.007***
	(0.003)	(0.003)	(0.006)	(0.002)
ScoreLeader × SameCity	0.087*	0.111*	0.135*	0.135**
	(0.045)	(0.058)	(0.074)	(0.059)
ScoreLeader × WhollyForeignOwned		0.001		-0.001
		(0.004)		(0.009)
ScoreLeader × SameCity × WhollyForeignOwned		-0.032		0.000
		(0.081)		(0.124)
Observations	78,097	78,097	77,788	77,788
Partialling out:				
Firm FE	✓	✓		
Category-Year FE	✓	✓	✓	✓
Firm-Category FE			✓	✓

Notes: The dependent variable is the quality of a domestic part suppliers. We consider all pairs of domestic and foreign/JV firms. The unit of observation is a pair-part category-year. Both the leader and follower scores are residualized after taking out fixed effects that are indicated at the bottom of the table. SameCity is an indicator variable that equals to 1 if the two firms are located in the same city. WhollyForeignOwned is an indicator variable that equals to 1 if the leader is a wholly foreign-owned firm and 0 if it is a joint venture. Standard errors are clustered at the follower-category and leader-category level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Appendices. For Online Publication Only

A A Simple Model of Knowledge Spillover

We write a simple learning model to guide the quantification exercise in Section 6. We make a couple of mild assumptions. First, we take the linear specification in Equation (2) literally and assume that the size of spillover among the affiliated pairs is proportional to the quality gap between the two. Second, for followers with multiple leaders, we use the average predicted quality. Finally, for illustration purpose, we also assume that domestic models (followers) benefits from knowledge spillover from affiliated JVs (leaders) every year. This is not crucial to the quantification exercise, and we present results without this assumption.

Formally, let q_t^k denote the observed quality of the follower in quality dimension k in year t. Let $\delta_t^k = \bar{\delta}_t + \varepsilon_t^k$ denote the baseline quality of the follower in dimension k in the absence of knowledge spillover. It consists of a component $\bar{\delta}_t$ common to all quality dimensions, and a dimension-specific component ε_t^k. Let Q_t^k denote the observed quality of a leader in quality dimension k and year t. It can be similarly decomposed into $\bar{Q}_t$ and μ_t^k, where μ_t^k measures quality-specific comparative (dis)advantage. Let ρ denote the intensity of spillover. We write:

$$q_t^k = \delta_t^k + \rho(Q_t^k - \delta_t^k) \tag{A.1}$$

$$= \underbrace{(1-\rho)\bar{\delta}_t + \rho\bar{Q}_t}_{\text{follower model-year FE}} + \rho\mu_t^k + (1-\rho)\varepsilon_t^k \tag{A.2}$$

Let ξ^k denote the follower's residualized quality scores in dimension k. It follows that:

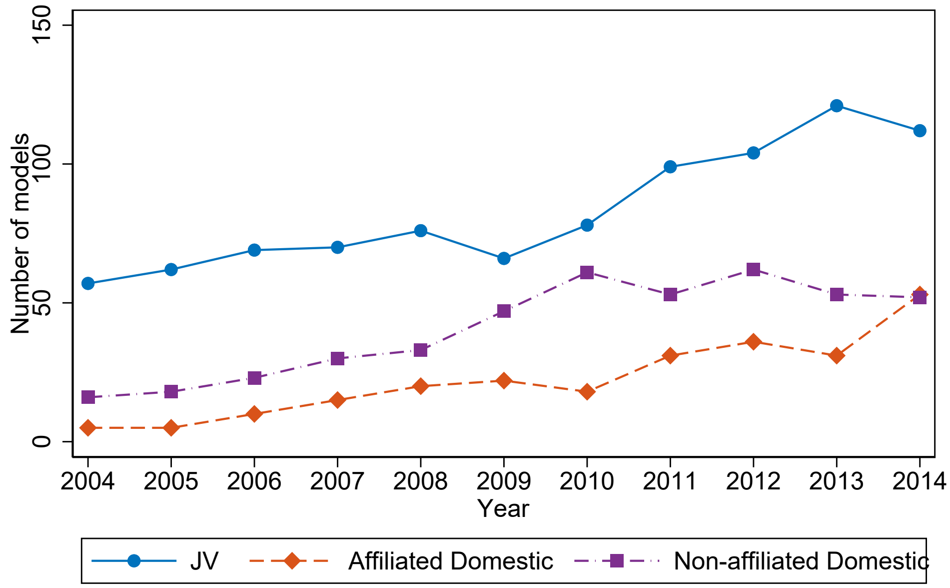
$$\xi_t^k = \rho\mu_t^k + (1-\rho)\varepsilon_t^k \tag{A.3}$$

This expression maps to our pairwise empirical framework. Intuitively, knowledge spillover translates into similar quality strength between the leader and the follower. ε_t^k, or the intrinsic quality strength of follower in the absence of spillover, shows up as a noise in the estimation. The identification assumption is that the follower's intrinsic quality strength ε_t^k is independent from the leader's quality strength μ_t^k. We examine and rule out potential threats to this assumption, such as endogenous JV formation, overlapping consumer base, and direct technology transfer in Section 4.2.

We impute the value of ρ using our reduced-form estimates, and use Equation (A.1) to back out knowledge spillover between each leader-follower pair in each year. For domestic models with multiple leaders, with calculate average spillover from the set of leaders. The reduction in quality of a follower when *quid pro quo* was lifted in 2009 s the sum of spillover between 2009 and year t.

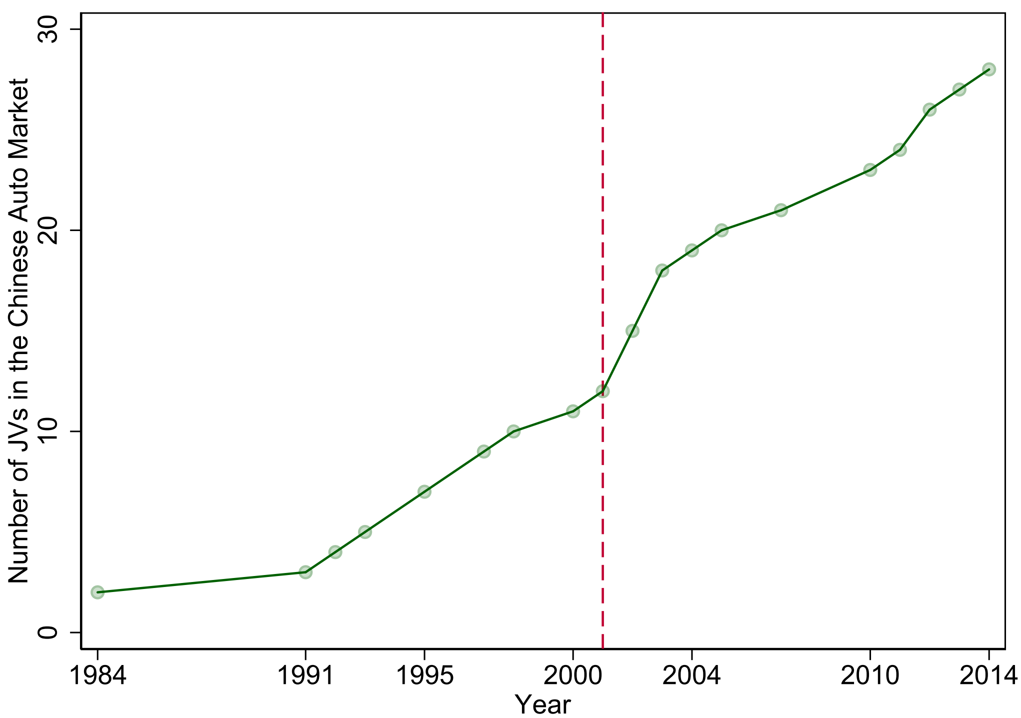
B Figures and Tables

Figure B.1: Entry of Models by Ownership Over Time



Notes: Affiliated domestic firms are the domestic automakers that have joint ventures with foreign automakers. They are all SOEs. The number of models from these automakers indicates the indigenous brands, i.e., brands produced solely by the domestic automakers. Non-affiliated domestic automakers are those automakers that do not have joint ventures.

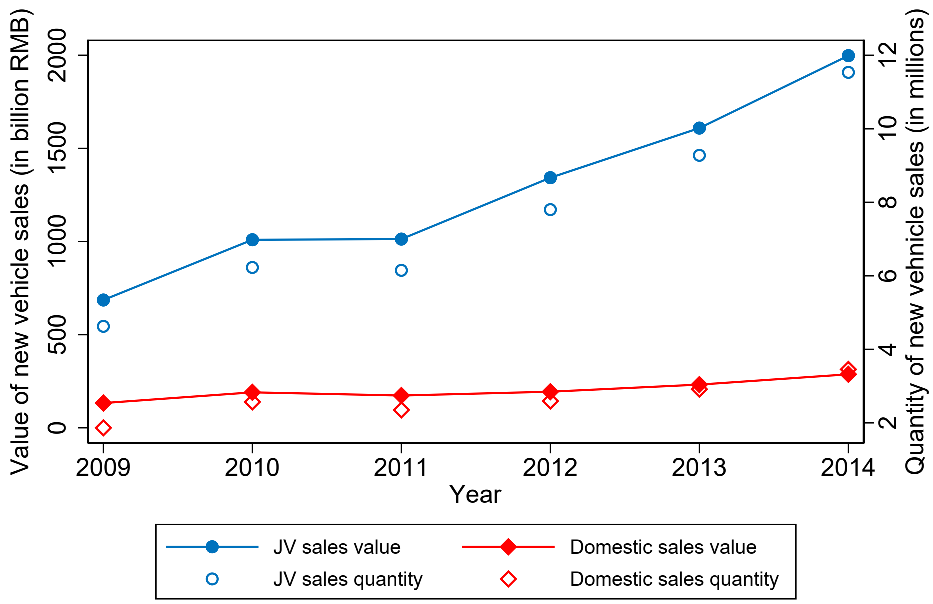
Figure B.2: Entry of International Joint Ventures



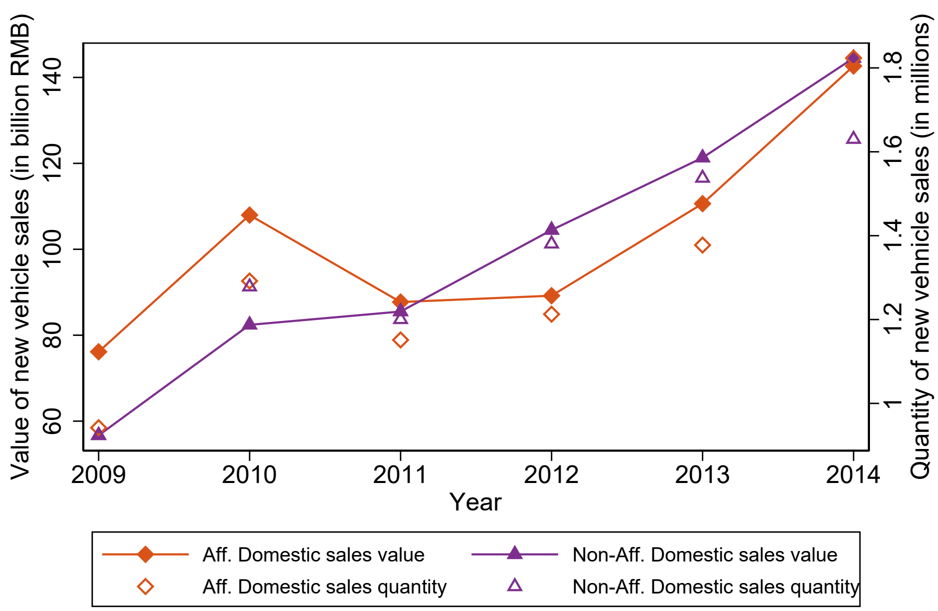
Notes: The figure plots the number of JVs in the Chinese auto market over time. Significant entries include: (1) 1984-1994: VW-Shanghai, VW-FAW, PSA-Dongfeng, Suzuki-Changan; (2) 1994-2000: GM-Shanghai, Honda-Guangzhou, Toyota-FAW, Suzuki-Changhe; (3) post 2000: Ford-Changan, Nissan-Dongfeng, Hyundai-Beijing, BMW-Brilliance.

Figure B.3: Growth of the Chinese Auto Industry by Ownership Type

Panel A. Performance of JVs and Domestic automakers

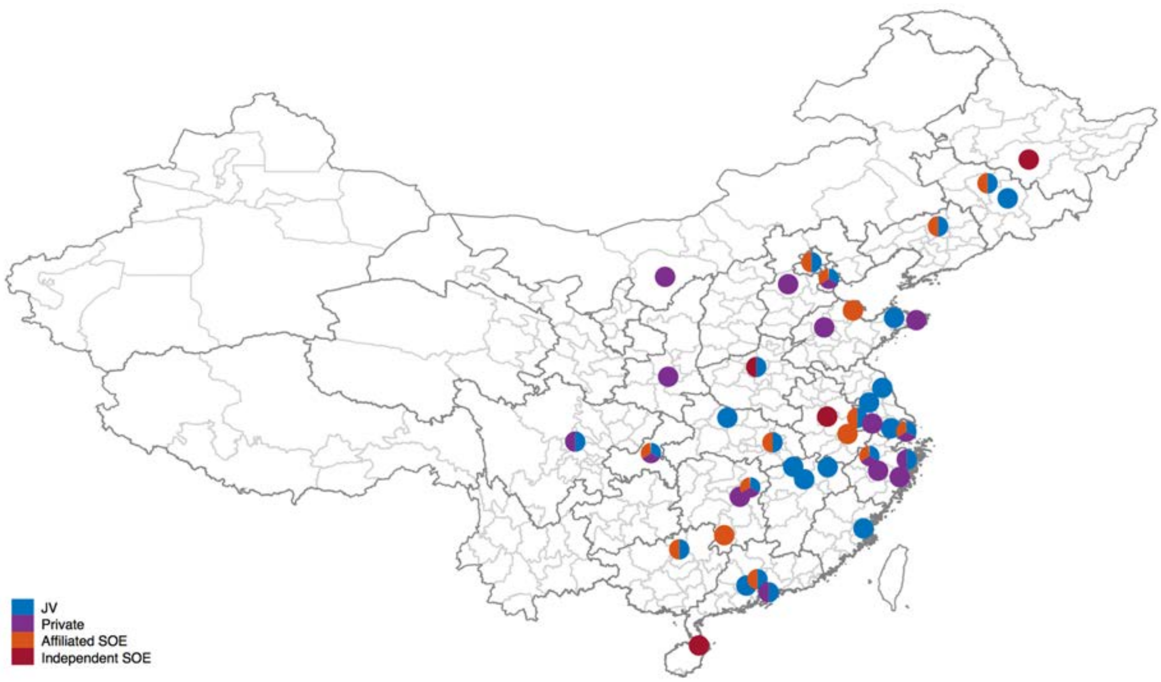


Panel B. Performance among Domestic automakers



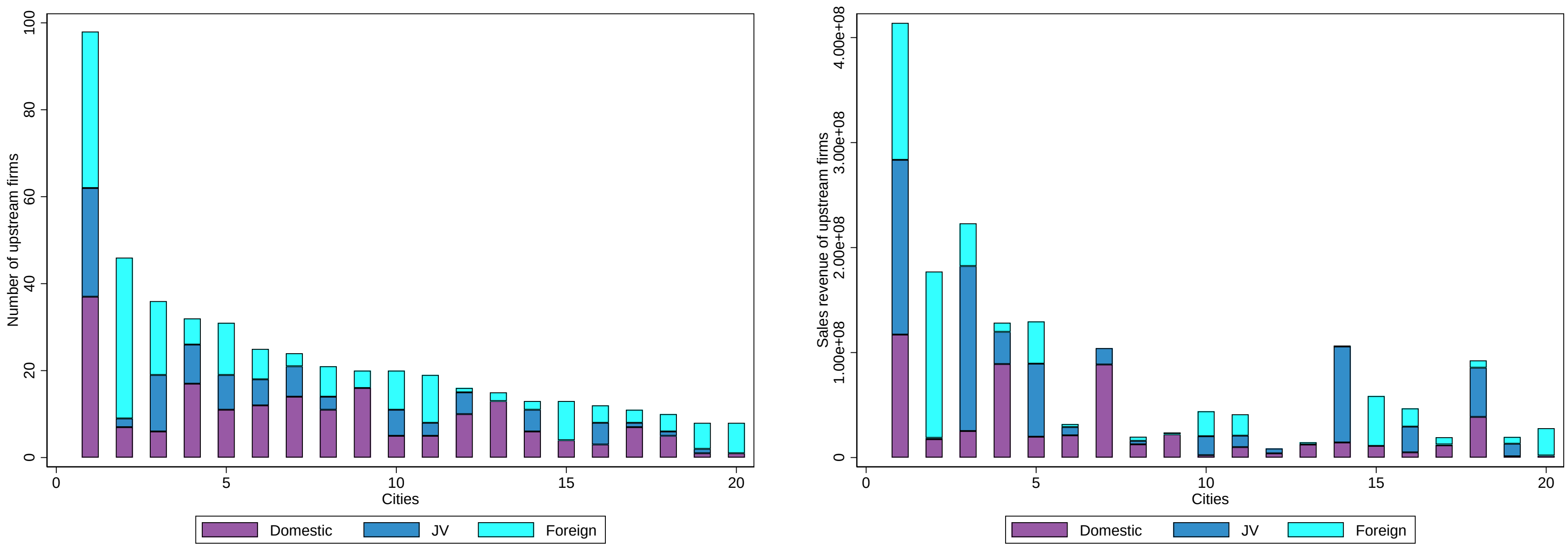
Notes: Sales value and quantity are calculated using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year, and does not include imported models, which account for around 3% of total sales.

Figure B.4: Geographical Distribution of Vehicle Production Plants in China



Notes: This figures shows a map of vehicle production cities in China. Each circle represents a city. Colors of the circle indicate the ownership composition of the production plants located in a given city.

Figure B.5: The Upstream Auto Parts Industry: Firm and Sales Distribution by Ownership Type



Notes: This figure shows the distribution of ownership types by the number of firms and sales revenue for the top 20 cities, defined in terms of total sales revenue from 2009 to 2014, using the NBS annual survey of manufacturing firms. Each bar shows the breakdown of ownership type in a given city.

Table B.1: Joint Ventures in the Chinese Passenger Vehicle Market

Joint Venture	Foreign Partner	Chinese Partner	2014 Sales	2014 Market share
VW-FAW	Volkswagen	First Auto Works	1668	.113
VW-Shanghai	Volkswagen	Shanghai Auto	1633	.111
GM-Shanghai	General Motors	Shanghai Auto	1510	.102
Hyundai-Beijing	Hyundai	Beijing Auto	1067	.072
Nissan-Dongfeng	Nissan	Dongfeng Motors	920	.062
Ford-Changan	Ford	Changan Auto	853	.058
Citroen-Dongfeng	PSA	Dongfeng Motors	658	.045
Toyota-FAW	Toyota	First Auto Works	568	.039
Kia-Yueda-Dongfeng	Kia Motors	Dongfeng Motors	562	.038
Honda-Guangzhou	Honda	Guangzhou Auto	424	.029
Toyota-Guangzhou	Toyota	Guangzhou Auto	333	.023
Honda-Dongfeng	Honda	Dongfeng Motors	297	.020
BMW-Brilliance	BMW	Brilliance Auto	259	.018
GM-Shanghai-Wuling	General Motors	Shanghai Auto	154	.010
Mercedes-Beijing	Daimler	Beijing Auto	147	.010
Suzuki-Changan	Suzuki	Changan Auto	143	.010
Mazda-FAW	Mazda	First Auto Works	94	.006
Suzuki-Changhe	Suzuki	Changhe Auto	87	.006
Mitsubishi-Southeast	Mitsubishi	Southeast Auto	69	.005
Fiat-Guangzhou	Fiat	Guangzhou Auto	60	.004
Mitsubishi-Guangzhou	Mitsubishi	Guangzhou Auto	49	.003
JMC	Ford, Isuzu	Jiangling Motors	43	.003
Landrover-Chery	Jaguar Land Rover	Chery		
Infinity-Dongfeng	Nissan	Dongfeng Motors		
Qoros	Israel Corporation	Chery		
Citroen-Changan	Citroen	Changan Auto		
Total			11598	0.79

Notes: This table shows the sales quantity and market shares of JVs in 2014. Sales are denoted in thousand. Landrover-Chery, Infinity-Dongfeng, Qoros, Ciroen-Changan had released models by 2014, but their sales was not captured by the License registrations data until 2015.

Table B.2: Location of Auto Assembly Plants in China

City	Province	JV	SOE	Private
Panel A. Northeastern Region				
Changchun	Jilin	Toyota-FAW, VW-FAW, Mazda-FAW	FAW	
Jilin	Jilin	Daihatsu-FAW		
Shanyang	Liaoning	GM-Shanghai, BMW-Brilliance	Brilliance	
Haerbin	Heilongjiang		Hafei	
Panel B. Northern Region				
Beijing	Beijing	Mercedes-Beijing, Hyundai-Beijing	BAIC, BAIC-Foton, Changan	
Tianjin	Tianjin	Toyota-FAW	FAW-Xiali	Great Wall
Boading	Hebei			Great Wall
Erdos	Neimenggu			Huatai
Panel C. Eastern Region				
Shanghai	Shanghai	VW-Shanghai, GM-Shanghai	SAIC, Chery	Geely
Hangzhou	Zhejiang	Ford-Changan	DF-Yulong, GAC-Gonow	Zotye
Ningbo	Zhejiang	VW-FAW		Geely
Taizhou	Zhejiang			Geely
Jinhua	Zhejiang			Zotye
Hefei	Anhui		JAC	
Wuhu	Anhui		Chery	
Dongying	Shandong		GAC-Gonow	
Weihai	Shandong			Huatai
Jinan	Shandong			Geely
Yantai	Shandong	GM-Shanghai		
Nanjing	Jiangsu	Ford-Changan, VW-SAIC	SAIC, Changan	
Changzhou	Jiangsu			Zotye
Yangzhou	Jiangsu	VW-Shanghai		
Yancheng	Jiangsu	Kia-Yueda-Dongfeng		
Suzhou	Jiangsu	Landrover-Chery		
Nanchang	Jiangxi	JMC		
Jiujiang	Jiangxi	Suzuki-Changhe		
Jingdezhen	Jiangxi	Suzuki-Changhe		
Panel D. Southern Region				
Guangzhou	Guangdong	Nissan-Dongfeng, Toyota-Guangzhou, Honda-Guangzhou, Citroen-Changan	GAC	
Foshan	Guangdong	VW-FAW		
Shenzhen	Guangdong			BYD
Liuzhou	Guangxi	GM-Shanghai-Wuling	Dongfeng-Liuzhou	
Haikou	Hainan		Haima	
Panel E. Central Region				
Zhengzhou	Henan	Nissan-Dongfeng	Haima	
Wuhan	Hubei	Honda-Dongfeng, Citroen-Dongfeng	Dongfeng	
Xiangfan	Hubei	Nissan-Dongfeng		
Xiangyang	Hubei	Infiniti-Dongfeng		
Changsha	Hunan	Fiat-Guangzhou, Mitsubishi-Guangzhou		BYD, Zotye
Xiangtan	Hunan			Geely, Zotye
Panel F. Southwestern Region				
Chongqing	Chongqing	Ford-Changan, Suzuki-Changan	Changan	Lifan
Chengdu	Sichuan	Toyota-FAW, VW-FAW		Geely
Panel G. Northwestern Region				
Xian	Shannxi			BYD

Table B.3: Summary Statistics: Standardized IQS and APEAL Scores

Ownership	JV						Domestic Firms					
Year	2009		2014		2009-2014		2009		2014		2009-2014	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: IQS scores												
IQS 1: Audio/entertainment/navigation	-.749	4.972	.687	2.367	-.345	5.403	-.587	5.128	1.285	1.924	.686	3.425
IQS 2: The driving experience	-.008	.898	.309	.461	.118	.681	-.289	1.446	.429	.235	-.235	1.41
IQS 3: Engine	.205	1.611	.34	1.513	.351	1.571	-1.094	1.512	.074	1.173	-.698	1.709
IQS 4: Features/controls/displays	-.226	3.507	.851	2.011	.111	3.893	.206	2.673	.461	2.86	-.22	3.854
IQS 5: HVAC problems	0	.835	.133	.452	.046	.819	-.418	2.024	.115	.528	-.092	1.282
IQS 6: Interior problems	.331	5.954	2.199	3.825	.984	5.607	-5.137	7.57	1.21	3.937	-1.955	7.074
IQS 7: Seat problems	-.099	3.072	.593	2.384	-.031	3.393	-.257	2.84	.512	2.047	.062	2.877
IQS 8: Transmission	-.147	3.278	2.416	1.658	1.101	2.827	-4.511	4.414	.988	2.105	-2.188	4.162
IQS 9: Exterior problems	-.288	4.434	1.486	2.685	.761	3.71	-4.504	6.581	.791	3.917	-1.513	6.098
IQS *average*	-.109	1.444	1.002	.767	.344	1.446	-1.843	1.393	.652	.821	-.684	1.747
Panel B: APEAL scores												
APEAL 1: Audio, entertainment, and navigation	1.168	9.048	.023	5.689	3.096	7.807	-10.845	10.333	-6.321	3.627	-6.151	7.278
APEAL 2: Engine and transmission	1.432	4.415	.357	3.028	2.105	4.021	-6.774	5.035	-3.609	1.867	-4.183	3.609
APEAL 3: Exterior	2.255	6.33	-1.557	4.82	2.228	6	-5.708	7.832	-6.825	2.717	-4.426	5.478
APEAL 4: Heating, ventilation, and air conditioning	2.363	7.484	-.756	5.142	2.881	6.953	-9.177	8.753	-6.411	2.851	-5.725	6.109
APEAL 5: Visibility and driving safety	2.135	7.219	-.945	5.15	2.928	6.923	-9.849	8.212	-6.58	2.953	-5.818	5.873
APEAL 6: Driving dynamics	2.61	6.962	-.637	5.125	3.007	6.673	-9.432	8.762	-6.415	3.281	-5.975	6.105
APEAL 7: Fuel economy	.189	1.675	-.094	1.191	.635	1.645	-2.213	1.701	-1.377	.832	-1.262	1.39
APEAL 8: Interior	3.118	14.183	-1.389	9.003	4.754	12.106	-15.22	14.729	-11.23	4.914	-9.446	10.29
APEAL 9: Seats	1.267	14.283	-.259	8.941	4.759	12.181	-16.513	16.003	-9.386	5.124	-9.455	11.025
APEAL 10: Storage and space	2.054	9.518	-1.395	6.437	3.027	8.629	-9.6	11.508	-7.985	3.881	-6.014	8.229
APEAL *average*	1.859	7.822	-.665	5.327	2.942	7.064	-9.533	8.889	-6.614	3.021	-5.845	6.193
Average across all quality scores	.927	4.426	.124	2.882	1.711	3.785	-5.891	4.59	-3.172	1.701	-3.4	3.45
Num of firms	19		25		26		14		15		19	
Num of models	76		119		146		37		50		102	

Notes: This table summarizes the standardized IQS and APEAL scores. IQS scores are multiplied by negative one so that a higher score indicates better quality, as do APEAL scores. We first standardize all the survey responses under a given dimension by stacking all model-year observations together and compute the z-score for each question. The standardized z-scores are then aggregated to the dimension level.

Table B.4: Dynamic Spillover Effects with a Balanced Panel

	(1) Lag 0	(2) Lag 1	(3) Lag 2	(4) Lag 3
JVScore	0.005	0.001	0.002**	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
× SameGroup	-0.043	-0.024	-0.031***	-0.112***
	(0.033)	(0.020)	(0.005)	(0.020)
× SameSegment	-0.033***	-0.013***	-0.012***	-0.020***
	(0.002)	(0.004)	(0.003)	(0.002)
× SameSegment × SameGroup	0.258***	0.230***	0.164***	0.178***
	(0.092)	(0.066)	(0.054)	(0.036)
Observations	71,478	59,565	47,652	35,739
Partialling out:				
Model-Year FE	✓	✓	✓	✓
Dimension-Year FE	✓	✓	✓	✓
Dimension-Segment FE	✓	✓	✓	✓

Notes: This table replicates the specification in Column (2) of Table 3 using leaders' quality measures in the past. We restrict the sample to the set of models that are on the market for all six years during our sample period. Column (1) repeats the baseline regression and Column (2) uses leaders' quality measures in the previous year as the explanatory variable. Columns (3) and (4) are based on leaders' quality measures two or three years ago. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table B.5: Knowledge Spillover: Fixed Effect Models

	(1)	(2)	(3)	(4)	(5)	(6)
JVScore	-0.002	-0.003	-0.003	-0.004*	-0.003	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\times$ SameGroup	0.045*	0.022	0.025	0.029	0.025	0.024
	(0.025)	(0.024)	(0.022)	(0.027)	(0.025)	(0.027)
$\times$ SameSeg		0.005	0.003	0.004	0.001	0.005
		(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
$\times$ SameGroup $\times$ SameSeg		0.140***	0.112***	0.159***	0.140***	0.169***
		(0.022)	(0.019)	(0.026)	(0.022)	(0.026)
Observations	591280	591280	591280	591280	591280	591280
Fixed Effects:						
Firm FE	✓	✓				
Firm-year FE			✓		✓	
Model FE				✓	✓	
Model-year FE						✓
Dimension-year FE	✓	✓	✓	✓	✓	✓
Dimension-Segment FE	✓	✓	✓	✓	✓	✓

Notes: This table replicates the specifications in Table 3 using one-step estimation with fixed effects. The JV and domestic scores are standardized IQS and APEAL scores without partialling out fixed effects. All firm, model, and segment fixed effects are defined at the follower-leader pair level. Standard errors are clustered at FollowerFirm-Dimension and LeaderFirm-Dimension level. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table B.6: Knowledge Spillover: Alternative Clustering of Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
Clustering:	DomesticFirm-Dimension JVFirm-Dimension		Domestic-JVFirmPair-Dimension		Domestic-JVFirmPair-Dimension DomesticFirm-Dimension-Year, JVFirm-Dimension-Year	
JVScore	-0.002	-0.002	-0.002	-0.002	-0.002*	-0.002*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
× SameGroup	0.028**	0.004	0.028*	0.004	0.028***	0.004
	(0.014)	(0.013)	(0.015)	(0.014)	(0.011)	(0.011)
× SameSeg		0.003		0.003		0.003
		(0.002)		(0.006)		(0.003)
× SameGroup × SameSeg		0.138***		0.138***		0.138***
		(0.021)		(0.025)		(0.020)
Clustering:	DomesticFirm JVFirm		Domestic-JVFirmPair		Domestic-JVFirmPair DomesticFirm-Year, JVFirm-Year	
JVScore	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.010)	(0.009)	(0.003)	(0.003)
× SameGroup	0.028	0.004	0.028	0.004	0.028	0.004
	(0.033)	(0.033)	(0.064)	(0.058)	(0.059)	(0.054)
× SameSeg		0.003		0.003		0.003
		(0.003)		(0.017)		(0.008)
× SameGroup × SameSeg		0.138***		0.138**		0.138***
		(0.048)		(0.067)		(0.052)
Partialling out:						
Model-Year FE	✓	✓	✓	✓	✓	✓
Dimension-Year FE	✓	✓	✓	✓	✓	✓
Dimension-Segment FE	✓	✓	✓	✓	✓	✓

Note: Number of observation is 591,280 for all columns. This table replicates Column (6) in Table 3 under six alternative clustering of the standard errors. Columns (1) and (2) in the top panel cluster the standard error two-way at domestic firm-quality dimension and JV firm - quality dimension levels. Columns (3) and (4) in the top panel cluster the standard error at domestic-JV firm pair-quality dimension level. Columns (5) and (6) in the top panel cluster the standard error three-way at domestic-JV firm pair-quality dimension, domestic firm-quality dimension-year, and JV firm-quality dimension-year levels. Columns (1) and (2) in the bottom panel cluster the standard error two-way at domestic firm and JV firm levels. Columns (3) and (4) in the bottom panel cluster the standard error at domestic-JV firm pair level. Finally, Columns (5) and (6) in the top panel cluster the standard error three-way at domestic-JV firm pair, domestic firm-year and JV firm-year levels.