Quid Pro Quo, Knowledge Spillover, and Industrial Quality Upgrades: Evidence from the Chinese Auto Industry

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Abstract

This paper studies the impact of FDI via *quid pro quo* (technology for market access) in facilitating knowledge spillover and quality upgrades. 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, compared to their nonaffiliated counterparts, adopt more similar quality strengths of their joint venture partners. *Quid pro quo* generates knowledge spillover to affiliated domestic automakers in addition to any industry-wide spillover. We rule out alternative explanations involving endogenous joint venture network formation, overlapping customer bases, or direct technology transfer via market transactions. Analyses leveraging additional micro datasets on worker flows and upstream suppliers demonstrate that labor mobility and supplier networks are important channels mediating knowledge spillover. Finally, we estimate an equilibrium model for the auto industry and quantify the impact of *quid-pro-quo*-induced quality upgrading on domestic sales and profits. *Quid pro quo* improved the quality of affiliated domestic models by 3.8-12.7% and raised their sales (profit) by 0.9-3.9% (1.02-3.49%) between 2007 and 2014 relative to unrestricted FDI.

Keywords: FDI, knowledge spillover, product quality, joint venture

JEL classification: F23, O14, O25

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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 international organizations (UNCTAD, 2018; World Bank, 2018).[1] Nevertheless, for strategic reasons, emerging economies such as China, India, and Brazil continue to impose considerable restrictions on foreign direct investment (FDI) in certain sectors. 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 strict cap on the share of foreign equity, in return for access to the host country's domestic market (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 at the forefront of the U.S.–China trade tensions, and concern over this policy was a key stated justification for the Trump administration's decision to impose tariffs on $50 billion worth of Chinese imports in 2018.[3]

Despite the policy relevance of *quid pro quo* and these recent controversies, little is known about its benefits to the host country over a policy of unrestricted FDI.[4] The famous fiasco of the GM-Toyota JV in the 1990s suggests learning need not materialize for hosting countries for reasons such as limited absorptive capacity and cultural differences. The vast literature on FDI has paid relatively scant attention to whether and how the *form* of FDI matters. In this paper, we attempt to fill this knowledge gap by examining the effectiveness of the joint venture requirement under *quid pro quo* in facilitating knowledge spillover from foreign to domestic firms. Unlike previous studies that mostly rely on firm-level total factor productivity (TFP) as the outcome variable, we exploit a rich set of product quality attributes that embody firms' fundamental technological capabilities. These quality measures allow us to look inside the black box of TFP and provide concrete evidence of knowledge spillover. In addition, a better understanding of industrial quality upgrades is valuable in itself and relevant for both academics and policy makers in developing countries (Verhoogen, 2020).

[1] Restrictions on foreign investment and technology transfer were common in developing 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 imposes 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 U.S. 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 through foreign ownership restrictions is considered a key component of China's technology transfer regime. Source: https://ustr.gov/sites/default/files/Section 301 FINAL.PDF.

[4] While it seems natural that joint ventures should facilitate knowledge spillover, effective learning may not necessarily materialize. One example is New United Motor Manufacturing, Inc. (NUMMI), a joint venture between GM and Toyota between 1984 and 2010. GM executives attempted to spread the Toyota Production System to its other assembly plants in the US, but it proved largely unsuccessful after over two decades of joint ventures. A full story can be found in 561: NUMMI (2015) - This American Life.

Our context is the Chinese automobile industry, the largest in the world since 2009. Foreign automakers are required to set up joint ventures (the *quid*) with domestic automakers to produce and sell cars in China (the *quo*). A fixed cap of 50% is imposed on the foreign ownership share, and it is binding in all cases. There are 23 joint ventures (e.g., BMW–Brilliance), 12 domestic automakers that are affiliated with the joint ventures but have independent production (e.g., Brilliance Auto),[5] and 7 domestic automakers with no joint venture affiliation (e.g., BYD).

The automobile industry is the paradigmatic industry for studying knowledge spillover given the multitude of technological and quality features embodied in the final products. Our primary dataset consists of rich quality measures along multiple dimensions of vehicle performance, including both malfunction rates and driver experience ratings, for nearly the universe of car models produced in China from 2001 to 2014.[6] We map these granular quality data onto the entire ownership network to trace knowledge flow patterns. To examine potential channels of knowledge flow, we leverage additional data sets on worker flows among automakers, parts and components suppliers, patent transfers, and auto assembly plant locations. To our knowledge, this represents one of the most comprehensive data of China's automobile industry, spanning a period of unprecedented growth from its near-nascence to being the world's largest auto market.

We begin by documenting the quality catch-up among Chinese domestic automakers. Malfunction rates of car models produced by domestic automakers fell by more than 75% from 2001 to 2014, demonstrating impressive quality improvement. At the same time, the quality gap between domestic models and JV models produced in China narrowed greatly: while the malfunction rate of domestic models was 65% higher than that of JV models in 2001, by 2014, this gap had shrunk to 33%.

While many factors may explain the overall quality upgrading of the industry, including industry-wide knowledge spillovers from 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 through JVs. These domestic automakers are the primary beneficiaries of the policy, receiving direct exposure to foreign technology.[7] Therefore, to isolate knowledge spillover as a result of ownership affiliation under *quid pro quo*, relative to unrestricted FDI without joint ownership requirements, we examine whether affiliated domestics automakers ("followers") learn more from their affiliated foreign automakers ("leaders") than do nonaffiliated domestic automakers.

To identify learning and knowledge spillover, we leverage our rich multidimensional quality data

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

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

[7]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 facilities when setting up a JV.

and examine whether affiliated domestic followers adopt JV leaders' quality strengths 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. Toyota–FAW, a JV between the Japanese automaker Toyota and the domestic automaker First Auto Work, produces Toyota models that are fuel efficient. We examine whether Brillaince produces indigenous models with better engine performance and FAW produces more fuel-efficient models relative to indigenous models produced by other domestic automakers.

Our analysis takes advantage of detailed quality measures along multiple dimensions and exploits *within-model relative* quality across dimensions. Specifically, the main specification controls for the *overall* quality of each model in each period. This accounts for potential endogenous JV formation, whereby foreign and domestic automakers strategically choose each other as partners based on overall quality. In addition, it also controls for industry-wide technological progress in different quality dimensions (e.g., fuel-saving technologies) and the quality strengths common across vehicle segments (e.g., better safety features in the luxury segment).[8] We find that when a JV model scores one standard deviation higher on a quality dimension, the indigenous models of the affiliated domestic automaker in the same vehicle segment score 0.087 standard deviations higher on the same dimension than the models from other domestic automakers do.

We address a series of alternative explanations. While our main specification accounts for JV formation based on *overall* quality level, one may be concerned about endogenous JV formation based on *relative* strengths. For example, domestic automakers may seek foreign partners that are strong on certain quality dimensions to compensate for their own weaknesses or augment their advantages. To address this issue, we first exploit an institutional feature by limiting our sample to JVs formed in the 1980s and 1990s. At that time, China's passenger vehicle market was in its infancy. Most domestic automakers had scant technological knowhow in passenger vehicle production. Therefore, it is unlikely that JV partners were matched based on quality strengths. Nevertheless, the pattern of shared quality persists for this subsample. To further examine any initial selection in JV formation, we focus on JVs formed after 2000, for which we observe the quality performance of the leader and follower models from the very beginning of the partnership formation. If anything, affiliated partners tend to exhibit negative association in relative quality strength when the JV was formed, and only become similar over time. This pattern further supports to the learning and knowledge spillover interpretation: it takes time for affiliated domestic automakers to learn from their foreign partners; hence, similarity in relative quality strength only emerges over time.

Next, we consider the role of geographic proximity. To the extent that production facilities of

[8] Following the standard classification system, we group models into eight segments: mini sedan, small sedan, compact sedan, medium sedan, large sedan, small-medium sport utility vehicle (SUV), large SUV, and multipurpose vehicle (MPV). Quality is measured in different dimensions such as the engine, transmission, and interior, as discussed in Section 2.2.

JVs and their affiliated domestic firms are sometimes located close to one another, the patterns of knowledge spillover could be partly driven by geographic proximity rather than ownership affiliation per se. Exploring the *partial* overlap between the ownership and geographical networks, we show that while spillover between affiliated pairs produced in the same province is the strongest, there remains substantial knowledge spillover from JVs to affiliated domestic firms located in different provinces.

Another confounding factor is that affiliated partners might target the same set of consumers and hence design similar products. However, analyses using household vehicle ownership surveys indicate that most car buyers do not consider models from JVs and affiliated domestic partners to be close substitutes. JV models are concentrated in high-end markets, while domestic models tend to target the low-end markets. Additional robustness checks alleviate concerns over other confounding demand-side factors including brand image spillovers. Lastly, we show that the observed patterns of shared quality strength are not driven by explicit market transactions such as patent transfers: only 27 out of over 10,000 patent transfers in China's auto industry originated from a JV.

All together, the reduced form results are indicative of learning and knowledge spillovers from JVs to their affiliated automakers. Next, we examine two potential mechanisms for this spillover—worker flows and supplier networks—both of which are documented in the literature. As carriers of technology knowhow, workers move across automakers and serve as a conduit of knowledge spillover.[9] We construct worker flows between each JV–domestic automaker pair using data from LinkedIn (China). We find significantly higher rates of worker flows between affiliated pairs than nonaffiliated pairs. Flows from JVs to affiliated domestic automakers, rather than the reverse, are associated with knowledge spillover. In addition, the strength of the spillover increases with the share of high-tech workers (engineers and designers) in these flows. The estimates imply that the additional worker flows that domestic automakers receive from affiliated JVs can explain up to 54% of knowledge spillover from ownership affiliation.

We next investigate the role of parts suppliers, motivated by the observation that high-quality parts and components directly affect the performance of the downstream vehicles. JVs' high quality standards could enhance the performance of domestic parts suppliers. If affiliated domestic automakers source from the same set of parts suppliers that serve JVs, they could directly benefit from the "shared supplier spillover" (Kee, 2015).[10] Using supplier network data from MarkLines, we calculate the number of common part suppliers shared by JV–domestic model pairs. JVs and affiliated domestic firms have greater supplier overlap than nonaffiliated firm pairs, which can explain up to 65% of knowledge spillover

[9] 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 works documenting this mechanism between foreign multinationals and domestic firms include Balsvik (2011); Görg and Strobl (2005); Poole (2013); Fosfuri, Motta, and Rønde (2001).

[10] A large body of work documents 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 ownership affiliation.

Finally, we turn to quantify the impact of *quid pro quo* on domestic quality upgrades and firm profit. Based on the estimates discussed above, *quid pro quo* improved the quality of domestic affiliated models by 3.8-12.7% from 2007 and 2014.[11] To translate the quality changes into sales and profits, we estimate a structural model of automobile market equilibrium to recover consumers' willingness to pay for quality. The improved quality as a result of *quid-pro-quo*-induced knowledge spillover translates to 0.9%-3.9% more sales and 1.02-3.49% higher profits for affiliated domestic models between 2007 and 2014. Overall, we find that while *quid pro quo* facilitates quality upgrading relative to the unrestricted FDI, its overall impacts on domestic quality, sales and profits are modest. In light of the trade dispute between China and the U.S., these findings suggest that China's recent policy change to remove the joint ownership requirement may not significantly hinder quality upgrades and sales performance of Chinese domestic automakers.

We acknowledge several caveats and highlight potential directions for future research. First, our study focuses on the benefits of *quid pro quo* for domestic firms but does not speak about the costs to foreign firms in terms of either the profit split or potential IP infringement risks. Understanding the former takes us one step closer to evaluating the full costs and benefits of the industrial policy and speaks to the current policy debate. Second, 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 firms' incentives to introduce products and technology and more generally firms' incentives to organize global supply chains in light of the global knowledge spillover.(Antràs and Chor, 2013; Buera and Oberfield, 2016; Bilir and Morales, 2016).

Our work contributes to several strands of the existing literature. First, it speaks to the extensive empirical literature on FDI spillover. We refer interested readers to Harrison and Rodríguez-Clare (2009) for an excellent review. We highlight three key contributions to this literature. First, we focus on whether and how the *form* of FDI matters, beyond its mere presence. Second, methodologically, we propose a new identification strategy that exploits rich within-product quality measures to control for industry-wide and firm-level potential confounders.[12] Lastly, we look beyond TFP and study the impact on quality upgrading using product-level quality attributes that embed firms' technological capability.[13]

[11] We choose 2007 as the baseline year since all of the major JVs had been formed by then. This allows us to focus on knowledge spillovers conditioning on the set of existing market participants.

[12] Existing work has relied mostly on cross-industry variation in the presence or intensity of FDI 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 driven by 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. More recent work has tried to deal with this challenge by leveraging external shocks (e.g., through tariff reforms as in McCaig, Pavcnik, and Wong (2020) and foreign entry induced by the shocks.

[13] Most existing 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; Jiang et al., 2018).

Second, our paper relates to the growing body of work in trade and development that aims to elucidate the importance of technological innovation and quality upgrades for economic growth (see Verhoogen (2020) for an excellent review). The existing literature focuses mostly 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); Macchiavello and Miquel-Florensa (2019); Hansman et al. (2020); Bai et al. (2020)) to identify knowledge spillovers and examine the impact of FDI on domestic quality upgrades in developing countries.

Third, our study speaks to an emerging literature on the impacts of government-initiated technology transfers (Giorcelli, 2019; Bianchi and Giorcelli, 2022) and industrial policies (Kalouptsidi, 2017; Wollmann, 2018; Igami and Uetake, 2019; Chen et al., 2019; Barwick, Kalouptsidi, and Zahur, 2019; Lane, 2022) on firm behavior, innovation, and growth. 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).

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 launched its reform and opening policy in 1978, the country was an economic and technological backwater. China's automobile manufacturing was low tech, with limited capacity. It had virtually no production of passenger vehicles.[14] To develop its domestic automobile sector, the Chinese government allowed international automakers to enter the market but required them to partner with domestic firms to set up production facilities. In forming JVs, foreign automakers offer knowhow and product lines as equity, which is capped at 50%, while domestic partners provide manufacturing facilities and labor.[15] There are two key rationales for the policy. The first is to protect young and small domestic producers in nascent industries. The second is to allow domestic firms to learn from their

[14] The industry's total production was only 146,000 units of heavy trucks and 2,600 units of passenger vehicles in 1978.

[15] In 1978, China's First Ministry of Machinery, in charge of automobile production, invited major international automakers to visit China and negotiated terms of 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 his Chinese hosts. The proposal to use 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 longstanding policy. Source: https://media.gm.com/media/cn/zh/gm/news.detail.html/content/Pages/news/cn/zh/2011/Aug/0802.html.

foreign partners and enhance domestic technical capabilities.

The first joint venture for automobile manufacturing was set up in 1983 between American Motors Corporation (AMC, later acquired by Chrysler Corporation) and Beijing Jeep Corporation Ltd. (now Beijing Automotive Industry Corporation [BAIC]). In 1984, Volkswagen joined Shanghai Tractor Corporation (now Shanghai Automotive Industry Corporation [SAIC]) to form a second JV in the country. 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 consisted of "knockdown kit" assembly and relied almost exclusively on imported parts. As a result, technology transfer was limited.

Prior to 2000, most affiliated domestic automakers relied on JVs for the production of passenger vehicles.[16] There were few indigenous brands in the country prior to 2000, as shown in Figure D.1. In 2004, the central government announced an explicit goal of developing domestic automotive technology and promoting indigenous brands by supporting the establishment of R&D facilities with 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 for both domestic sale and export. Under these government policies, affiliated domestic automakers started to launch their own passenger vehicle brands. 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, affiliated domestic automakers had caught up with nonaffiliated domestic automakers in product offerings.

Figure 1 presents a snapshot of the ownership network of the Chinese auto industry in 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. Likewise, a single domestic firm might have multiple foreign partners. In total, there are seven large affiliated groups, as shown by the dotted blocks in Figure 1. To avoid complications related to 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 cars, while VW–FAW sells Audi and Jetta brands. There is no product-line overlap between any pair of JVs. All affiliated domestic automakers during our sample period are SOEs. Nonaffiliated domestic automakers (those without foreign partners) include both SOEs and private firms.

The industry 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, with China surpassing the US in 2009 to become the world's largest car market.[17] In 2017, China alone accounted for more than 33% of global auto production and sales. The industry was highly competitive, with 48

[16] Most nonaffiliated domestic automakers did not start production till after 2000.

[17] Passenger vehicles include sedans, SUVs, and MPVs. Minivans and pickup trucks are considered commercial vehicles.

firms producing more than 10,000 units in 2014. The number of JVs also increased steadily (Figure D.2): by 2007, most major international automakers had launched JVs in China. Table D.1 lists the JVs and their sales and market shares in 2014. While JVs dominated the industry, the sales of domestic firms had also grown over the past decade (Figure D.3). This is especially true in the SUV segment, where the market share of domestic firms grew from 27% to 36% between 2009 and 2014.

Under WTO rules, explicit technology transfer requirements for market access are not permitted. Hence, *quid pro quo* in China has mostly been carried out implicitly via ownership restrictions on joint ventures to facilitate technology transfer from foreign firms. As part of China's broad industrial policy, it is considered by some countries to create unfair advantages for domestic companies. Because of the emphasis on technology transfer, this policy has been criticized as a state-sponsored effort to 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 was most often felt in strategically important industries such as aerospace (44%) and chemicals (41%).[18]

Amid recent trade tensions with the U.S., the Chinese government pledged to further open its automobile market by lifting the foreign ownership cap by 2022, representing a major shift away from the *quid pro quo* policy after around four decades. This will effectively allow foreign automakers to have solely owned production facilities in China. Following the pledge, BMW and its domestic partner Brilliance reached an agreement whereby BMW would pay Brilliance $4.1 billion to increase BMW's ownership share in the joint venture from 50% to 75% by 2022. Some have speculated that this could impact not only the Chinese market but also the global industry. Understanding the role played by ownership affiliation is a crucial step toward 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 J.D. Power between 2001 and 2014.[19] Between April and June each year, J.D. Power recruits subjects who have purchased a vehicle in the past year in over 50 cities in China and surveys their user experience during the first six months of vehicle ownership. The survey covers the major passenger vehicle models in China, which account for over 90% of the market share in terms of sales. The total number of survey respondents for 2014 is 18,884 and around 110 car owners per model. The IQS study reports

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

[19] The IQS survey was launched in 2001, and the APEAL survey was launched in 2003.

the number of problems experienced per 100 vehicles during the first 90 days of ownership. The survey asks more than 200 questions, covering a complete spectrum of vehicle functionalities, which fall under nine quality dimensions: exterior problems, driving experience, feature/control/displays, audio/entertainment/navigation, seat problems, heating/ventilation/air conditioning (HVAC) problems, interior problems, and engine and transmission problems.[20] Industry experts believe that initial quality is an excellent predictor of long-term reliability, which has a significant impact on owner satisfaction and brand reputation. The APEAL study elicits user satisfaction ratings over 100 vehicle quality attributes, which are grouped into 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.[21]

Figure 2 presents the relationship between vehicle prices and the two quality measures. Panel A plots prices against the IQS, with the left figure controlling for vehicle size and horsepower/weight (a proxy for acceleration) and the right figure further controlling for year, segment, and ownership type fixed effects. Panel B shows the relationship between prices and the APEAL with the same controls. The tight correlations between price and the IQS/APEAL indicators provide strong evidence that these are credible measures of vehicle quality, with high-quality 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 contain 52,898 LinkedIn users who have worked in 60 JVs and domestic firms. The spatial distribution of these users is consistent with that of automobile production: the correlation coefficient between the number of LinkedIn users in a province and that province's automobile production for 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.[22]

We identify 4,099 users who moved at least once from one automobile company to another. For each job switch, we compile information on the 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 we drop observations with missing location data. Of these, 617 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 parts supplier network is compiled from MarkLines's Who Supplies

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

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

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

Whom database.[23] MarkLines started collecting data in 2008, but most of the supplier information is available only for models produced after 2012. Since data at the annual level are sparse, we pool information from all years to construct the supplier network. Our final sample covers 1,378 distinct part suppliers, 271 vehicle parts under 31 part categories, and 459 vehicle models.[24] Each auto parts company supplies on average 2.8 parts for 11 vehicle models, and there are 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 are not complete enough to be regarded as a census of suppliers, they provide valuable information on the production network and capture the major parts suppliers.

Geographic location of auto plants We identify the plant location of each model using information from auto firms' official websites (Table D.2). Figure D.4 maps vehicle models to their production cities. Each circle represents a city. Colors of the circle indicate the ownership composition of all models produced in a given city. There is a partial overlap between the ownership and location networks. For example, Dongfeng, one of the largest affiliated SOE firms, has a plant in the same city, Wuhan, as one of its JVs' plants (Honda–Dongfeng). It also has a plant in Liuzhou, which does not host any of its JVs. At the same time, Geely, a private firm with no JV affiliation, has a plant in Shanghai, which hosts two joint ventures (VW–SAIC and GM–SAIC). Our empirical analysis explores this partial overlap between ownership and geographical networks to assess the role of both in mediating knowledge flow.

Patent database Data on patent transfers are collected by China's State Intellectual Property Office and cover the universe of patent transfers between firms from 2001 to 2018. 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 quality preferences.

2.3 Descriptive Quality Upgrade Patterns

We begin by documenting descriptive quality upgrade patterns across ownership types. J.D. Power's raw IQS scores report malfunction rates of parts and components and represent an objective measure

[23] MarkLines collects supplier information in a number of ways. Some information is directly sourced from supplier companies or downstream assembly firms. Some is obtained from vehicle teardowns, where supplier information is retrieved from the label or stamp on vehicle parts. Press releases and news articles are another important data source.

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

of vehicle performance.[25] Figure 3 plots the dramatic improvement in the overall IQS score during the sample period, summed across all nine quality dimensions, for JVs, affiliated SOEs, and nonaffiliated domestic automakers, respectively (note that a smaller number of defects indicates higher quality). In 2003, JVs had significantly higher quality than the other two carmaker types: the number of defects per 100 vehicles was 278 for JV models, in contrast to 508 for models produced by affiliated domestic firms and 349 for those produced by nonaffiliated domestic firms. By 2014, the overall IQS score of the domestic models had largely converged to that of JVs: the number of defects per 100 vehicles was 94 for JV models, 123 for models from affiliated domestic firms, and 134 for those from nonaffiliated automakers. Our empirical strategy seeks to isolate the role of ownership affiliation under *quid pro quo* in driving the quality improvement of domestic models from other confounders.[26]

Table 1 reports the summary statistics of IQS and APEAL scores by year and ownership type for each of the quality dimensions. Since the raw IQS and APEAL scores (the malfunction rates) differ substantially in magnitude across different quality dimensions, we separately standardize the responses for each of the IQS survey questions and APEAL questions using all model-year observations. Then, we aggregate the standardized z-scores to the nine IQS dimensions and ten APEAL dimensions. There is significant heterogeneity in quality performance across different dimensions among firms within an ownership type, a key source of variation that 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 ownership affiliation stipulations under *quid pro quo* in addition to any industry-wide learning and quality improvements. Therefore, we look for differential spillover from JVs to affiliated domestic firms, relative to the spillover received by nonaffiliated domestic firms. As knowledge spillover is rarely observed, we use similarity in product quality strengths 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 than nonaffiliated models in these same dimensions, *ceteris paribus*, we take this as an indication of knowledge spillover via ownership affiliation.

[25] On the other hand, APEAL scores, measuring consumer satisfaction, may be affected by consumer perceptions and could evolve over time as consumers become more knowledgeable about quality. As shown in Table 1, the over-time improvement in APEAL is much more modest compared to the improvement in IQS.

[26] Given that all affiliated automakers are SOEs and most nonaffiliated ones are private, it is difficult to isolate the impact due to "quid pro quo" from the observational data since these two groups of firms are very different in terms of their ownership structure, efficiency level, competition incentives and growth dynamics (e.g., Song, Storesletten, and Zilibotti (2011); Brandt et al. (2017)).

However, the complicated ownership structure among JV and domestic partners discussed in Section 2.1 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 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 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). We proceed in two steps. First, we construct the residualized (i.e., relative) quality strengths for model i in vehicle segment s for quality dimension k in year t by partialing out fixed effects for model-year it (e.g., BMW–Brilliance X3 in 2014) and segment-dimension-year skt (e.g., engine of small-medium SUV in 2014):

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

The rich set of product-level and temporal fixed effects in Equation (1) helps mitigate common unobservables that affect quality improvement. Model-by-year fixed effects (λ_{it}) absorb time-varying changes that affect overall model quality. λ_{skt} captures differential quality strength of different vehicle segments and how that evolves over time. For example, it allows for greater engine power of SUVs compared to sedans, and accounts for industry-wide improvements in engine performance over time. $\widetilde{\text{Score}}_{ikt}$ captures model i's relative strength in a quality dimension k in year t, after we partial out model-year and segment-dimension-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 nonaffiliated domestic automaker (e.g., BYD F3). We regress follower i's relative quality 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 affiliated 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 strengths (or weaknesses) and contemporaneous comovement in quality (net of the overall time trend). Our identification strategy is best illustrated with a specific example. Figure 4 shows the engine quality and fuel efficiency of four models, two from JVs (BMW–Brilliance and Toyota–FAW) and two from the affiliated domestic automakers (Brilliance and FAW). The JV model from BMW–Brilliance has stronger engine performance but is less fuel efficient than the model from Toyota–FAW. The two domestic models produced by Brilliance and FAW exhibit similar relative strengths, consistent with learning. Our empirical analysis below examines whether such patterns hold systematically.

Our empirical framework represents a significant departure from the approaches used in existing literature on knowledge spillover from FDI to domestic firms, which mainly rely on TFP variation at the industry level along with the inclusion of 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 standard panel fixed effects may be inadequate in controlling for industry-time-level shocks that affect both the entry/performance of foreign firms and that of domestic firms, such as government policies targeting certain industries. By focusing on different dimensions of quality strength *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 absorb industry-wide quality improvements. Therefore, if spillover from JVs benefits both affiliated automakers and nonaffiliated automakers by the same magnitude, the estimate of β_1 does not capture this— rightly so—as industry-wide spillover does not pertain to ownership affiliation and thus should not be counted as the benefit due to *quid pro quo*.

Finally, the two-step procedure in Equations (1) and (2) has advantages over the standard one-step estimation where one regresses a follower's quality on a leader's quality with all the fixed effects. First, it allows us to control for the time-varying average quality of the domestic and JV models separately. As discussed above, the ability to absorb time-varying unobservables at the firm and product level and isolate the relative quality strength is a key contribution to the existing literature. The standard one-step estimation only controls for followers' average quality. Second, as shown by Lee and Lemieux (2010), under mild conditions, partialing out fixed effects first could potentially increase the efficiency of the key parameter estimates β_1 while maintaining consistency. We present our main results based on the two-step estimation procedure and perform robustness checks with the standard one-step fixed effect model in Section 4.1.

3.2 Evidence of Relative Strengths

Before we move to the main analysis, we test a key premise for our empirical analysis: models produced by different JVs indeed have differential quality strengths that domestic firms can learn from. Figure 5 graphically illustrates 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 strengths among models produced by the same JV firm, we first estimate Equations (1) and (2) using JV pairs only. 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, compute the residualized scores for each JV model and regress the follower scores on the 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 the similarity in relative quality strengths between JV and domestic models.

As shown in Table 2, the coefficient on the interaction term with SameFirm is positive and statistically significant, indicating that models produced by the same firm exhibit similar qualiaty strength.[27] The magnitude is also economically meaningful. When we include 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 3.1 defects in the same quality dimension among other models by the same firm. The coefficient is stable across the 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 do indeed specialize in different quality dimensions, which sets the ground for 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 738,948 observations. There are 13,946 distinct domestic–JV pairs, and 723 belong to affiliated pairs. We have nineteen quality metrics: nine IQS quality dimensions and ten APEAL performance dimensions.

Table 3 presents the estimation results for Equation 2. While our main specification incorporates model-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 different from that of nonaffiliated automakers.

[27] 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.

Column (1) partials out firm, dimension-year and dimension-segment FEs. The coefficient on JVScore captures the association in relative quality strengths between a random pair of nonaffiliated models.[28] The SameGroup dummy flags follower–leader pairs that come from JVs (e.g., Toyota–FAW) and their affiliated domestic partners (FAW). The interaction term between JVScore and the SameGroup dummy captures the association in relative quality strengths between affiliated models. Its coefficient is positive but statistically insignificant. When we further add interaction terms to flag pairs that belong to the same vehicle segment (SameSegment) in Column (2), we find that spillover occurs primarily among products in the same segment (e.g., sedan or SUV). The triple interaction term of JVScore, SameGroup and SameSegment is positive and significant at the 1% level, indicating that ownership affiliation enhances the spillover.

In light of the above finding, for the remaining empirical analysis, we 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 variation. The results remain robust. When we look at Column (6), our main specification (also the most demanding specification), the coefficient estimate of the interaction term is economically significant: 8.7% of the quality improvement observed in a JV model would be transmitted to the affiliated domestic models in the same segment. Another way to interpret the magnitude is to compare it with that in Column (6) of Table 2: the shared quality strength between affiliated JV–domestic pairs is 31% ($= \frac{0.087}{0.284}$) of that among models within the same JV firm.

Robustness checks: We perform three sets of robustness checks. First, we explore an alternative fixed effect regression specification. Our baseline empirical strategy is based on residualized quality measures after model-year and dimension-segment-year fixed effects are partialed out separately for leaders and followers. Table D.3 reports the results of running one-step fixed effect regressions that use the same combinations of fixed effects as in Table 3 as opposed to the two-step procedure. Mathematically, these regressions are not the same, but the estimates are similar, and all of them suggest that knowledge spillovers occur in the same segment and same group.

Second, we experiment with alternative clustering of the standard errors. The standard errors in Table 3 are two-way clustered by i's firm and quality dimension and 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 D.4 reports the standard errors clustered at six different levels, including 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.

[28]By construction, the association in relative quality strengths between a random pair of follower–leader models, including both affiliated and nonaffiliated models, is close to zero given that the sample consists of all possible follower–leader pairs in the same year. The absolute magnitudes of the coefficients on JVScore and JVScoreXSameGroup capture the association among nonaffiliated and affiliated pairs, respectively, and the gap between the two reflects the additional learning spillover to affiliated domestic models over the spillover to nonaffiliated domestic models.

Finally, we explore the impact of using leaders' lagged quality measures. For this exercise, we restrict the sample to the set of models on the market for at least four years during the sample period. The results are shown in Table D.5. Column (1) repeats the baseline regression for this subsample. The results are quantitatively similar to those in Column (6) of Table 3. Columns (2) to (4) lag a leader's quality score by one, two, and three years. The interaction coefficient between the past leader score and the dummy for the same group and same segment persists over time, but its magnitude gradually decays. The patterns are intuitive given that each generation of models mostly lasts for 3 to 4 years.

4.2 Alternative Explanations

The finding that domestic models mimic the quality strengths of their affiliated JV models is consistent with knowledge spillover. We now investigate several alternative interpretations, including endogenous JV formation, spillover due to geographic proximity, overlapping customer bases, and market transactions for technologies.

Endogenous JV formation One might be concerned that the ownership network—the set of domestic firms that form joint ventures with foreign auto producers—is not random. For example, to overcome their own weaknesses, domestic automakers may seek foreign partners who are strong on specific quality dimensions. The initial negative correlation in quality strengths 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 strengths, it would bias the estimates upward.

To address this issue, we first exploit an important institutional feature. Many major JVs in the Chinese auto industry were formed in the 1980s and 1990s, a period when domestic automakers had virtually no passenger vehicle production capacity. Their production of agricultural machinery (such as tractors) or heavy-duty trucks was low tech and relied on imports for key components. It was not until the mid-2000s when these domestic automakers started to develop their own indigenous brands. Therefore, in these early JVs, it would have been very difficult, if not impossible, for foreign automakers to predict the strengths/weaknesses of potential Chinese partners decades later, let alone to base their partnership decisions on those predictions. Table 4 Column (2) repeats our baseline specification while restricting the sample to JVs formed prior to 2000, which are unlikely to have been driven by strategic partnership considerations based on relative quality strengths for the reasons discussed above. If anything, compared to the baseline estimate in Column (1), spillover from these earlier JVs appears to be stronger. These results alleviate concerns over endogenous ownership formation and are consistent with the historical evidence on JV formation. Appendix A provides a brief history of two joint ventures and shows that the ownership decisions were made by the central government with no evidence of consideration of the relative technical strengths of either party.

Next, we turn to the relatively young JVs that were formed after 2000. Since our quality data spans from 2001 to 2014, it allows us to examine the quality performance of the affiliated domestic models at the very beginning of the joint venture formation. In particular, we can directly examine any initial association in relative quality strength between the affiliated partners and how the association evolves over time as the partnership ages. Column (3) of Table 4 shows that, if anything, the initial correlation in relative quality strengths between the affiliated partners appears to be negative, but that becomes less so over time and eventually turns positive after 10 years (this is consistent with positive interaction term in Column (2) for the older JVs, most of which were more than 10 years old at the beginning of our sample period). This pattern lends further support to the learning and knowledge spillover interpretation: it takes time for affiliated domestic automakers to learn from their foreign partners; hence, similarity in relative quality strength only emerges over time.

Spillover due to geographic proximity Existing literature has documented the role of geographic proximity in promoting spatially-mediated knowledge spillovers (Jaffe, Trajtenberg, and Henderson, 1993; Bloom, Schankerman, and Van Reenen, 2013). To the extent that production facilities of JVs and their affiliated domestic firms are sometimes located close to one another, the patterns of knowledge spillover could be partly driven by geographic proximity rather than ownership affiliation per se.[29] To examine this, we exploit the *partial* overlap between the ownership and geographical networks as shown in Figure D.4. We construct a dummy for two models in the same province and interact the ownership dummies (SameGroup and DiffGroup) with the location dummies (SameProvince and DiffProvince). Column (1) of Table 5 replicates the specification in Column (6) of Table 3 while focusing on follower–leader pairs in the same vehicle segment. Column (2) presents the full interaction between ownership and geography dummies. While spillover between affiliated pairs in the same province is the strongest, there remains substantial knowledge spillover from JVs to affiliated domestic firms in different provinces. This provides evidence that the knowledge spillover detected between affiliated pairs cannot be fully explained by geographic proximity.

Overlapping customer bases The observed similarity in relative quality strength may be partially driven by demand-side factors, as opposed to learning and knowledge spillover on the supply side. For example, models produced by affiliated automakers may be designed to target the same group of consumers who share similar taste, which then leads firms to specialize in similar quality dimensions. To examine this possibility, we leverage the household choices reported in the vehicle ownership survey (described in Section 2.2) to evaluate whether JVs and domestic automakers have overlapping customer bases. We estimate the following equation using a sample that consists of all pairwise combinations of

[29] In total, 267 out of 723 pairs of affiliated JV-domestic models are produced in the same province.

models in the same year:

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

where $\text{TopTwoChoices}_{ijt}$ counts the number of times that 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 to be 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. We control for whether the two models have the same segment, same ownership type, or same firm and for differences in price, size, and engine power.

The results in Table D.6 provide no evidence that affiliated model pairs are more likely to attract similar customers than a random pair of JV and domestic models, *ceteris paribus*. If anything, the estimates suggest that a pair of affiliated models in the same segment are slightly less likely to be listed as the top two choices. This is not surprising given that JV models are considerably more expensive than domestic indigenous models and target wealthier households.

Direct technology transfer The identified spillover effect might be driven by market transactions. For example, technologically advanced firms might sell or license their patents to firms that do not have the capacity to conduct R&D in house. A common challenge in the literature that studies the impact of FDI on knowledge spillover is that data on market transactions for technology transfer are rarely observed (Keller, 2004).

To address this concern, we obtain data on all patent transfers from the National Intellectual Property Administration (i.e., the Chinese Patent Office). For the period between 2001 and 2019, there are 1,208,325 records of patent transfers nationwide, of which 10,626 correspond to the auto industry (i.e., either the transferer or the transferee is owned by an auto assembly firm). Among the 10,626 cases of patent transfers, 68% are between a parent company and a subsidiary company or between two subsidiary companies under the same parent company. Only 27 cases originated from a JV. The lack of direct patent transfer from JVs to domestic firms is consistent with the finding in Holmes, McGrattan, and Prescott (2015) that JVs file a small number of patent applications in China in comparison to either Chinese domestic firms or foreign multinationals. Therefore, the observed patterns of spillovers are unlikely to be driven by market transactions of technologies.

In sum, we have shown that domestic models share similar quality strengths with affiliated JV models. The reduced-form findings support the interpretation of knowledge spillover via the ownership network. Next, we investigate potential mechanisms of this knowledge spillover.

5 Mechanisms of Knowledge Spillover

The vehicle production process includes interrelated stages from product planning (e.g., market analysis), to design and engineering (e.g., of the chassis, power train, exterior and interior), to the 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 through deliberate communication among partners, worker flows or shared parts suppliers. In this section, we examine worker flows and supplier networks as two potential mechanisms. 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 model pairs in different vehicle segments.

5.1 Worker Flows

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

We compile job switches from user profiles on LinkedIn (China) for the automobile sector.[30] We first document that workers are considerably more likely to move from JVs to affiliated SOEs. Among all workers who switched jobs from a JV to a domestic firm, 27.2% moved to the JV's affiliated domestic firm. This fraction would have been 9.3% if worker movements were random.[31]

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 6 summarizes the results. Column (1) shows that spillover is on average 10.3% between affiliated pairs in the same segment. Column (2) shows that spillover is 3.8% when worker flow is at the national average and increases by 2.3% for each standard-deviation increase in the volume of worker flow. The estimates suggest that worker flow explains 54% of the knowledge spillover from JVs to affiliated automakers.[32]

[30] Among job switchers who left a JV firm, 52.6% moved to another JV, and 47.4% moved to a domestic automaker. Among those who left a domestic firm, 36.8% moved to a JV, and 63.2% moved to another domestic automaker.

[31] To calculate this, we hold the number of workers moving from and to each firm fixed and assume that workers' propensity to move to a firm does not depend on where they move from. For example, if 200 workers move to firm A and 100 workers move to firm B in total, we assume that all workers are twice as likely to move to firm A regardless of which firm they move from.

[32] The difference in the average z-scores of an affiliated and a nonaffiliated pair is 2.43. Additional worker flow from JVs

Some underlying factors, such as closer connections between firms, could result in both larger worker flow and more knowledge spillover. Column (3) additionally controls for 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 flow, and no appreciable effect for domestic-to-JV flow. 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 conduct this estimate, we limit the sample to observations with positive JV-to-domestic flows and compute the share of technicians, classified based on job titles.[33] Consistent with the previous literature (e.g., Poole (2013)), we find that the strength of knowledge spillover increases with the flow of technicians from JVs to domestic automakers. Furthermore, we see that the flow of skilled workers benefits both affiliated and nonaffiliated domestic firms. This finding corroborates a popular view among industry experts that JVs have trained a large number of technicians for the Chinese auto industry, generating an important positive externality for both affiliated and nonaffiliated domestic firms. We lack statistical power to evaluate whether ownership affiliation itself confers an additional advantage.

While variations in worker flow across firms are not exogenous, the results provide suggestive evidence that worker flow plays an important role in mediating knowledge spillover. Our findings are also in line with the finding in Levitt, List, and Syverson (2013) that product defects in auto assembly plants are affected by the production experience stock embodied in plants' broader organizational capital, which could be affected by flow of workers with significant technical and managerial expertise. More generally, the findings are consistent with the existing literature that 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 flow of skilled workers transmits more knowledge than flow of nonskilled workers (Poole, 2013; Stoyanov and Zubanov, 2012b).

5.2 Supplier Network

The 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 vehicle performance. The presence of JVs has been argued to have helped and incentivized domestic parts suppliers to improve their product quality, benefiting domestic automakers.[34] JVs' sourcing decisions

to affiliated automakers contributes $2.43 \times 0.23 = 0.056$ or 54% of knowledge spillover (the baseline is 0.103).

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

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

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 so-called 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, in comparison to the average of 5.4 common suppliers between nonaffiliated pairs.[35] We examine the extent to which the shared quality strengths between affiliated pairs could be driven by common parts suppliers. For each model pair, we compute the Szymkiewicz–Simpson overlap ratio, which equals 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.[36] Table 7 reports the results. Columns (1) and (2) contain domestic–JV model pairs from all years from 2001 to 2014. Columns (3) and (4) restrict the sample to model pairs from 2012 to 2014 to account for missing information in the early years of the supplier network data (see Section 2.2). Overall, we see that larger supplier overlap is indeed associated with stronger knowledge spillover; this is true for both affiliated and nonaffiliated pairs. The estimates from Columns (3) and (4) imply that the greater supplier overlap among affiliated pairs can explain 65% of knowledge spillover via ownership affiliation.[37]

The importance of shared supplier spillover has been documented in the existing literature. For example, using variation in supplier networks generated by a trade policy shock in Bangladesh's garment industry, Kee (2015) finds that shared supplier networks explain about 1/3 of the productivity spillover from FDIs to domestic firms. Our results echo the earlier findings despite the different contexts.

6 Quantify the Impact of *Quid Pro Quo* on Domestic Upgrades

We end our analysis with a quantification exercise to evaluate the impact of *quid pro quo* on domestic vehicle quality, sales and profits. The exercise proceeds in two steps. The first step quantifies the impact of knowledge spillover due to the *quid pro quo*-induced ownership affiliation on domestic quality upgrades. The second step then translates the quality changes into impacts on sales and profits. This step estimates a structural model of the automobile market and conducts the counterfactual analysis on vehicle prices and firm profit when we remove the *quid pro quo*-induced ownership affiliation. We choose 2007 as the baseline year for the policy evaluation because all major JVs had formed by this point (see Figure D.2) and thus we can focus on knowledge spillovers conditioning on the set of existing market participants.[38]

[35] MarkLines focuses on first-tier suppliers. On average, a JV model has 64 suppliers and a domestic model has 32.

[36] We drop 3% of pairs for which at least one model has fewer than five distinct suppliers to reduce measurement error in the overlap ratio. The results are similar if we use the full sample.

[37] The difference in the average supplier overlap z-scores of an affiliated and a nonaffiliated pair is 1.06. Additional supplier overlap contributes $1.06 \times 0.037 = 0.039$ or 65% of knowledge spillover (the baseline is 0.06).

[38] Six small JVs with limited production entered after 2007. They accounted for 1.5% of market sales by 2014.

Since our empirical identification is based on relative quality strengths between followers and leaders, additional assumptions are needed to quantify 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 leader quality. Appendix B provides more details. It also illustrates how knowledge spillover of this nature translates into shared relative quality strengths between leaders and followers and that estimates based on relative quality strengths (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 knowledge spillover and learning that domestic affiliated firms experience in a given year are proportional to the difference between the JV model quality in that year and domestic model quality in 2007. The second scenario assumes that learning occurs cumulatively each year. The benefit that 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. 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 the results based on our baseline estimate in Table 3. We use the total IQS score as the quality measure of interest. The solid lines plot the observed annual average IQS scores for JV models, affiliated domestic models, and nonaffiliated domestic models. The dashed line plots the predicted quality of affiliated domestic models in the absence of *quid pro quo*, i.e., if the additional knowledge spillover due to ownership affiliation was shut down in 2007. In the first scenario, *quid pro quo* contributes to an average of 3.8% improvement in quality for affiliated models between 2007 and 2014 (around 5 fewer defects per model), and an average of 2.8% improvement in quality for all domestic models. With cumulative learning, the effect amounts to a 19.5% improvement (around 24 fewer defects per model) for affiliated models and a 12.7% improvement for all domestic models. Note that in both exercises, any industry-wide knowledge spillover due to the presence of foreign automakers is kept the same, as absorbed by model-year and quality dimension-segment-year fixed effects. Thus, the estimated effect purely captures the additional learning spillover due to ownership affiliation under *quid pro quo*.

To translate the impact on quality changes to sales performance of China's domestic automakers, we estimate an equilibrium model of vehicle demand and supply. Specifically, we extend the model in Barwick, Cao, and Li (2020) by allowing both demand and cost of production to depend on vehicle quality measured by IQS. Knowledge spillover under *quid pro quo* improves the quality of domestic models, and thereby influences the sales and profits of domestic automakers. We discuss details of the model and estimation results in Appendix C.

Our estimates suggest that conditional on prices and other key vehicle attributes, the elasticity of vehicle demand to IQS is about -0.60. Combined with the results on quality changes shown in Figure 6, this translates to a 0.9%-3.9% increase in sales of affiliated domestic models between 2007 and 2014, and a 0.5%-2.0% increase for all domestic models (equivalent to 330 and 1,120 million yuan, or $50 - $165 million in US dollar). Overall, these results suggest that while quid pro quo facilitates quality upgrading relative to the unrestricted FDI, its impacts on domestic quality, sales and profits are modest. In light of the trade dispute between China and the U.S., China's recent policy change to remove the joint ownership requirement may not significantly hinder quality upgrades and sales performance of Chinese domestic automakers.

7 Conclusion

This paper studies the effect of *quid pro quo*, the policy of requiring joint ownership in exchange for market access, in facilitating knowledge spillover from developed countries to developing countries. Leveraging unique datasets on quality ratings, supplier networks, worker flows, and household surveys, we document consistent patterns of additional knowledge spillover from JVs to domestic automakers as a result of *quid pro quo* beyond the general spillover induced by the presence of foreign automakers. Consistent with the existing literature, we find that worker flows and supplier networks are the primary channels of such knowledge spillover. On the other hand, the quantification exercise suggests that the ownership affiliation as a result of *quid pro quo* confers a modest benefit in terms of quality upgrades, sales and profits for domestic partners.

Our findings imply that the high-profile policy shift by the Chinese government to eliminate *quid pro quo* in automobile manufacturing starting from 2022 will unlikely have a large impact on quality dynamics and firm performance going forward. We end with an important caveat: our analysis abstracts away from potential endogenous changes in product offerings among foreign and domestic automakers in the absence of *quid pro quo*. With a majority stake or even sole ownership, foreign automakers may have stronger incentives to bring the most advanced technology into the Chinese market and offer a different set of products, as they can better guard their technology knowhow. How such incentives are shaped by global knowledge diffusion is an important open area for future empirical research.

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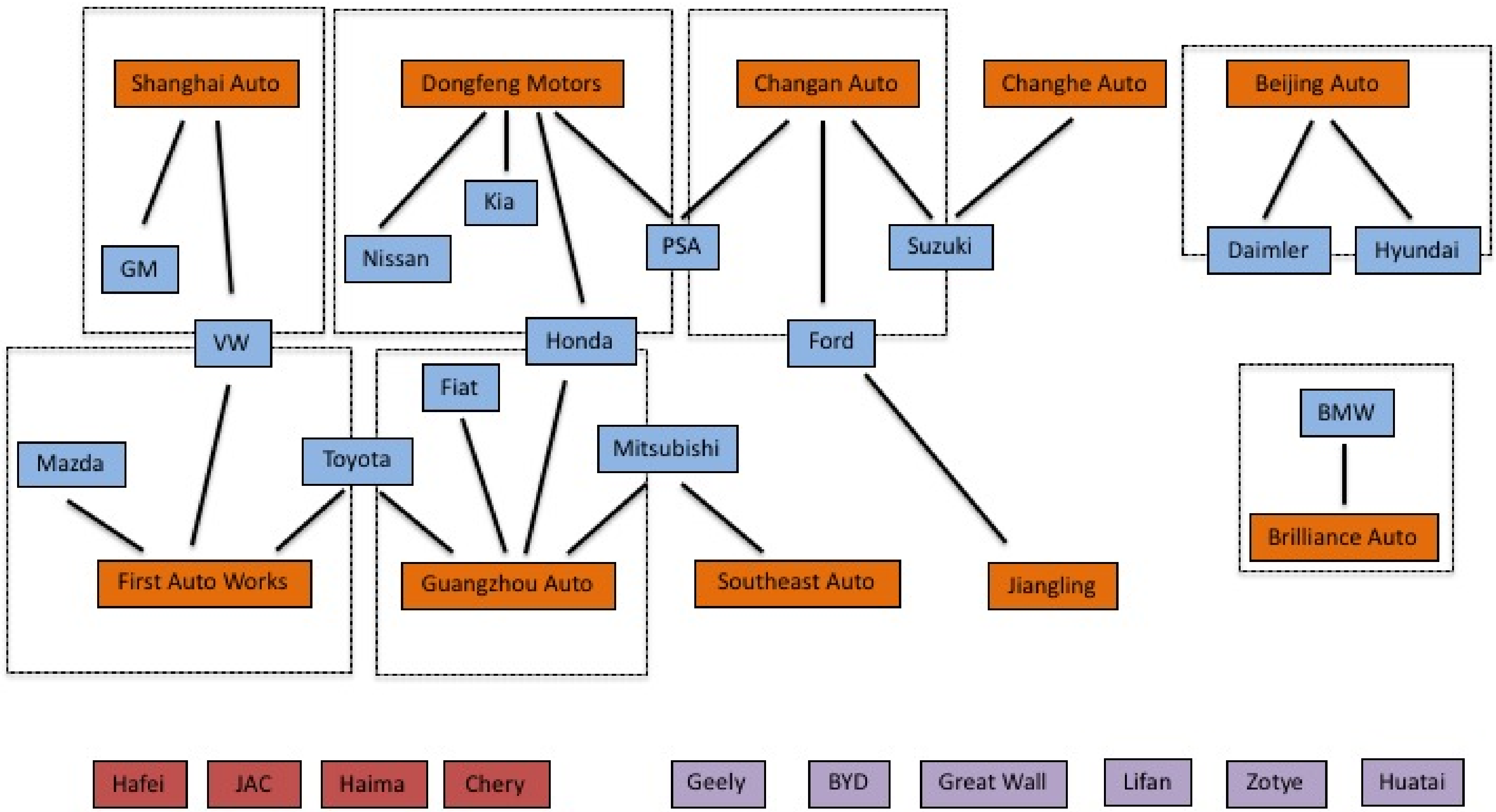
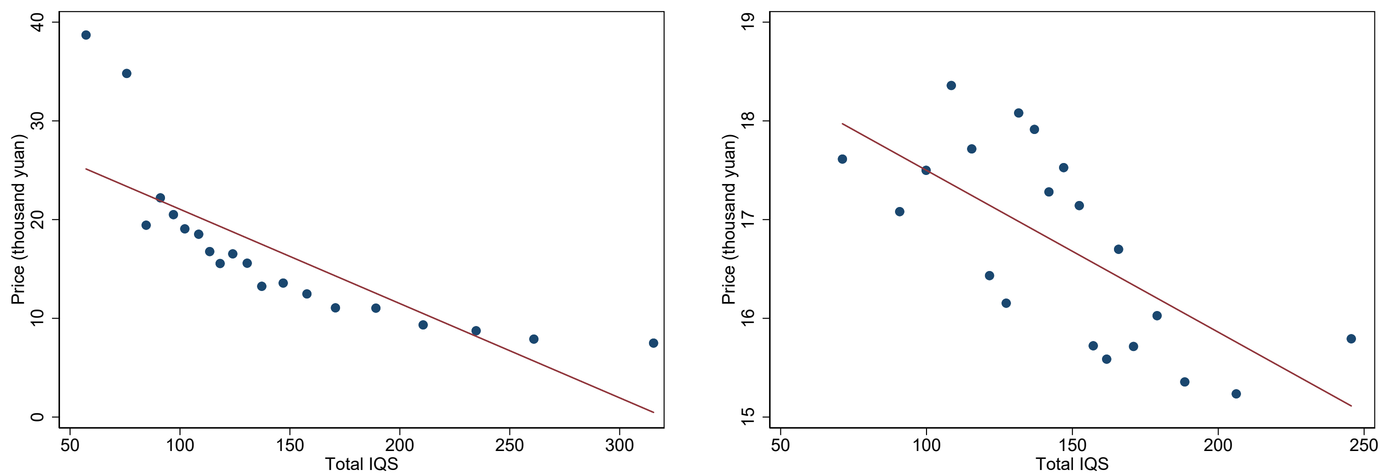
Figure 1: Joint Venture Network of the Chinese Auto Industry



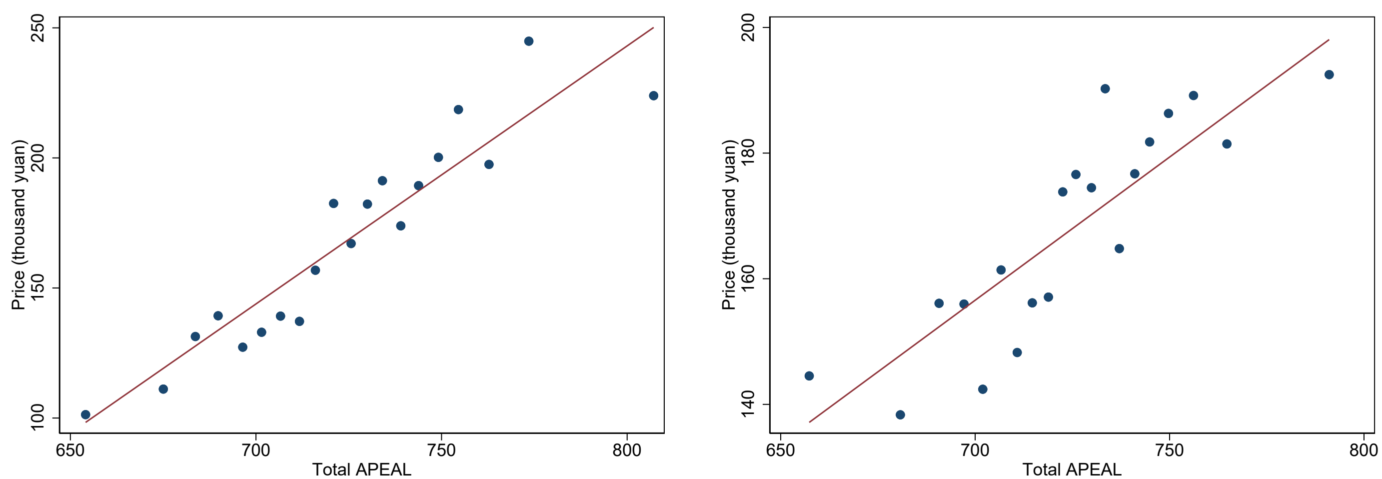
Notes: This figure is adapted from Figure 1 in Chen, Lawell, and Wang (2020). It describes the joint venture network of the Chinese auto market as of 2014. Orange boxes represent affiliated SOEs; blue boxes represent foreign partners in JVs; purple boxes represent private domestic automakers; red boxes represent nonaffiliated 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

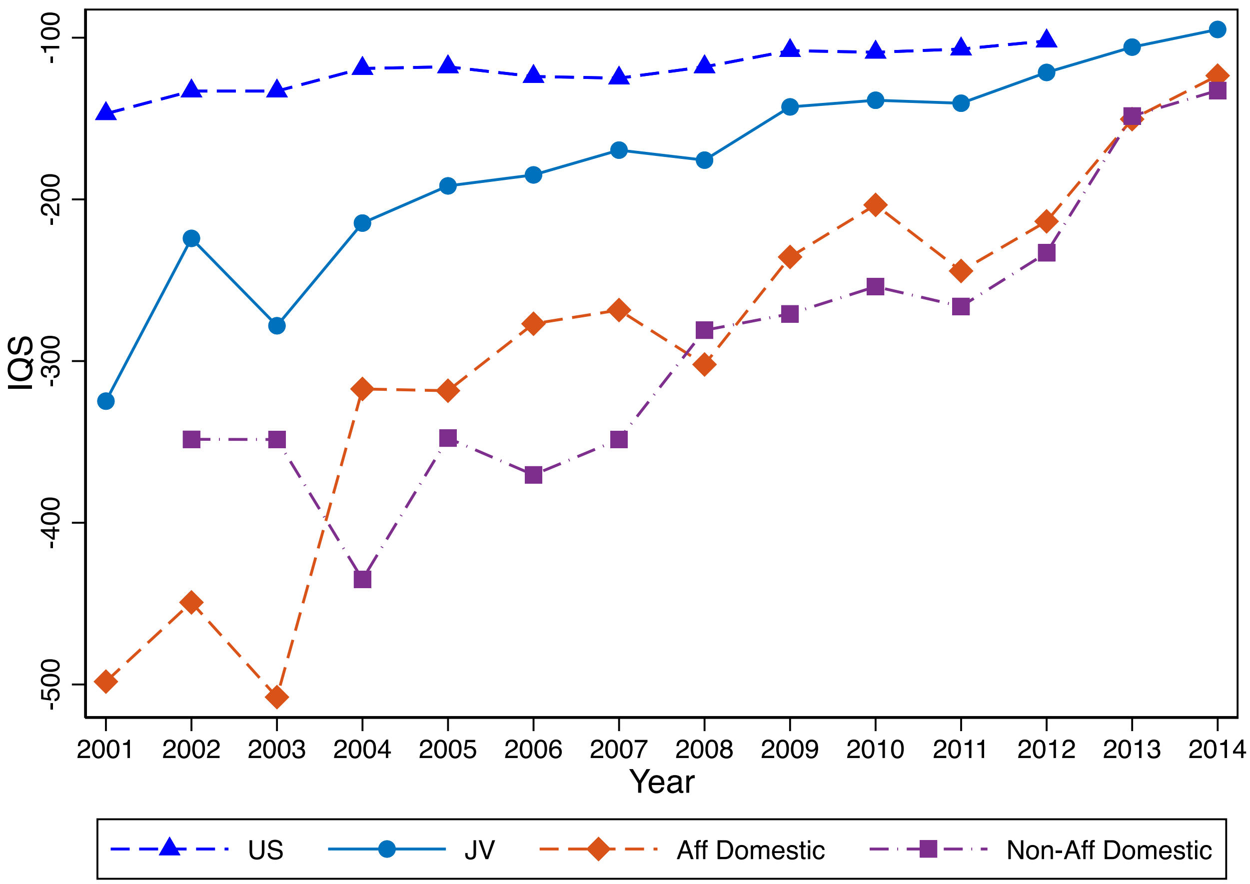


Panel B. Vehicle Price vs. APEAL



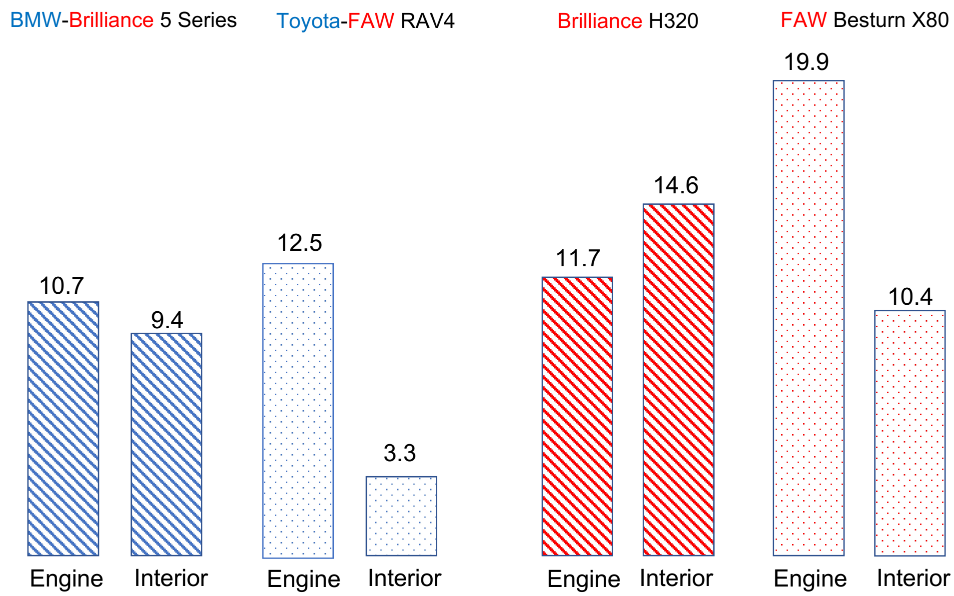
Notes: The figures are binned scatter plots between price and the IQS score (Panel A) and between price and the APEAL score (Panel B) based on data from 2009 to 2014. The price data are only available only since 2009. The left figures control for vehicle size and horsepower/weight. The right figures further add year fixed effects, segment fixed effects, and ownership type fixed effects. A lower IQS indicates fewer defects and hence better quality, while a higher APEAL indicates better quality.

Figure 3: Descriptive Patterns of Quality Upgrades



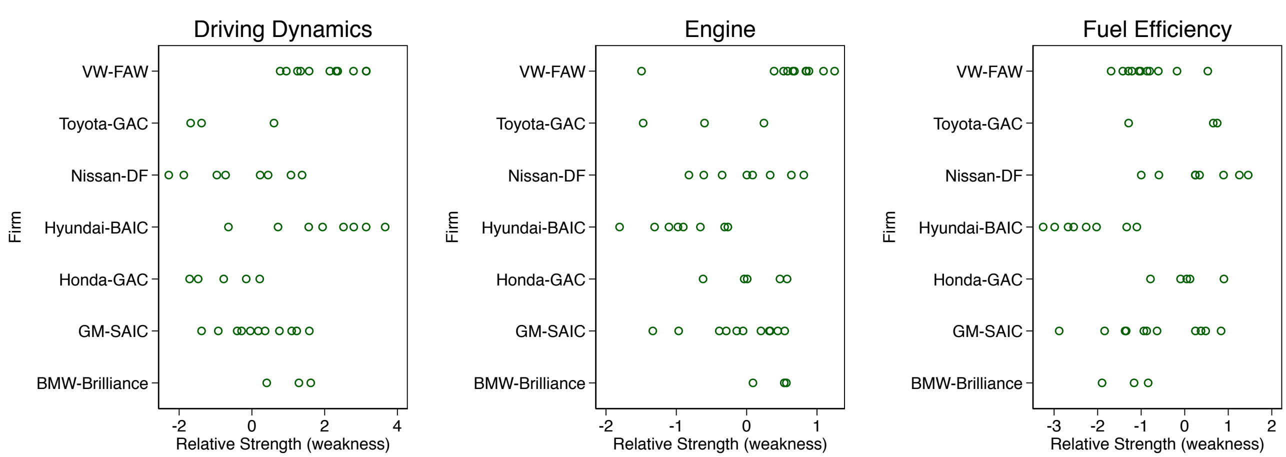
Notes: The vertical axis reports the IQS score, which is the total number of problems experienced per 100 vehicles during the first 90 days of ownership across nine performance dimensions. We multiply the IQS score with -1 so that higher values along the y-axis indicate higher quality (for example, -100 denotes a better quality than -300). The dark blue line on the top shows the average IQS scores of car models in the US, while the other three lines show IQS scores of cars under different ownership types in China. The US scores are truncated in 2012 because a new IQS questionnaire was adopted in the US market in 2013.

Figure 4: Leader–Follower Pattern of Relative Quality Strength



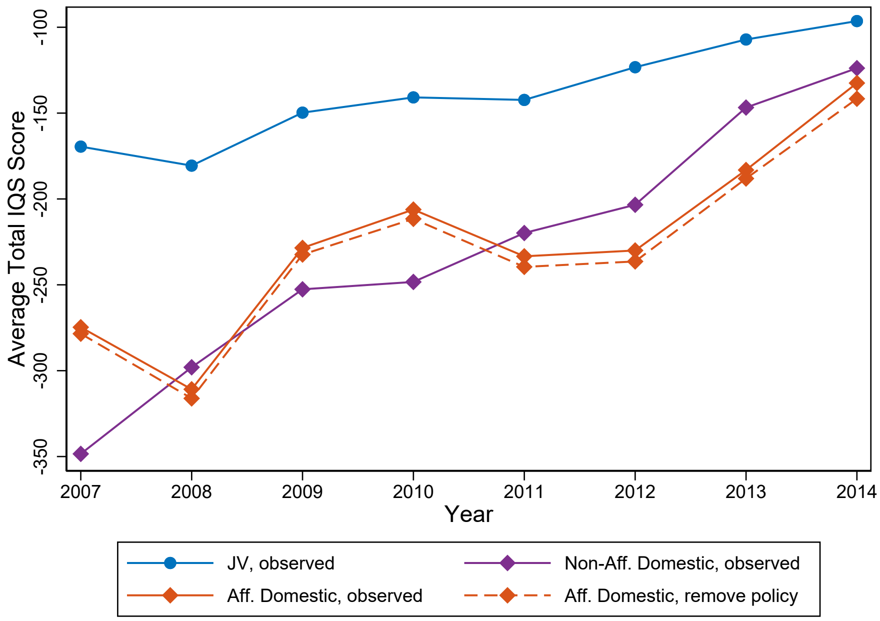
Notes: The bars show IQS quality scores for the engine and interior dimensions in 2014. The two models on the left are produced by JVs, and those on the right are indigenous brands produced by affiliated domestic automakers. A larger IQS score indicates more defects and lower quality. BMW has better engine performance; so does Brilliance. Toyota excels at interior design; so does FAW.

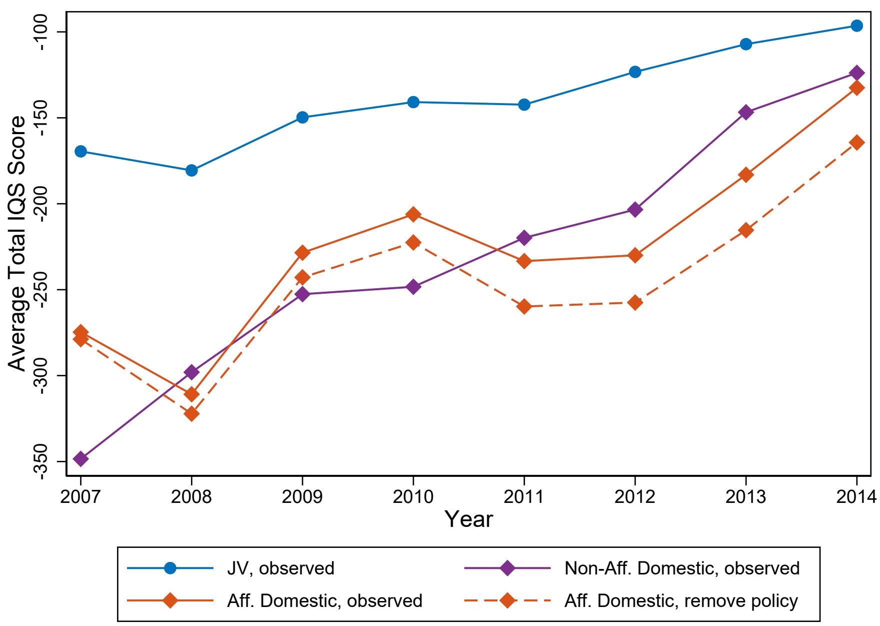
Figure 5: Differential Relative Quality Strengths among Leaders



Notes: This figure shows relative quality strengths (after model-year and quality-dimension-segment fixed effects are partialed out) across JVs along three vehicle performance dimensions measured in the 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.

Figure 6: Effects of Lifting *Quid Pro Quo* in 2007





Notes: The solid lines plot the observed quality improvement in terms of the total IQS score for JV and domestic models. The dashed line shows the counterfactual quality dynamics of affiliated domestic models if the *quid pro quo* had been lifted in 2006. The first panel assumes that knowledge spillover and learning that domestic affiliated firms experience in a given year are proportional to the difference between the JV model quality in that year and domestic model quality in 2007. The second panel assumes that learning occurs cumulatively each year. The benefit that 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				Nonaffiliated Domestic automakers			
Year	2003		2014		2003		2014		2003		2014	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: IQS scores												
IQS 1: Audio/entertainment/navigation	19.7	11.9	5.2	2.8	34.9	19.5	4.2	3.3	16.1	4.8	4.3	2.9
IQS 2: The driving experience	66.6	31.0	20.3	7.0	102.1	30.1	25.8	7.7	77.9	31.2	27.3	6.2
IQS 3: Engine	38.0	19.9	18.6	7.6	74.8	46.2	21.5	6.4	44.4	16.6	25.2	5.9
IQS 4: Features/controls/displays	25.8	30.7	9.8	3.4	39.1	30.3	12.3	6.3	36.5	22.5	12.6	4.4
IQS 5: HVAC problems	34.5	20.8	8.9	4.4	60.2	28.4	11.5	6.1	37.0	10.9	11.9	5.4
IQS 6: Interior problems	15.7	10.1	7.8	3.6	40.8	25.1	9.7	3.4	23.0	17.8	10.5	4.9
IQS 7: Seat problems	31.3	19.7	4.5	2.5	54.3	27.2	5.1	2.4	41.0	18.1	5.3	2.9
IQS 8: Transmission	20.6	16.1	7.1	4.7	44.1	9.0	12.8	4.1	26.4	19.2	16.5	4.6
IQS 9: Exterior problems	26.0	15.5	12.8	5.9	57.6	27.0	20.5	8.2	46.2	12.2	18.9	6.4
IQS *total*	278.1	132.0	94.9	22.8	507.8	222.7	123.4	24.3	348.5	126.8	132.6	19.7
Panel B: APEAL scores												
APEAL 1: Audio, entertainment, and navigation	79.3	5.4	97.4	19.3	73.3	5.1	93.4	15.8	76.1	4.6	90.9	15.0
APEAL 2: Engine and transmission	81.0	10.3	40.3	1.3	64.6	14.7	38.6	0.8	69.0	13.8	38.4	0.9
APEAL 3: Exterior	97.8	6.2	57.6	1.8	92.3	3.7	55.6	1.1	94.3	4.7	55.2	0.9
APEAL 4: Heating, ventilation, and air conditioning	89.9	5.6	64.6	2.1	82.6	4.7	62.3	1.2	88.9	7.1	61.9	1.1
APEAL 5: Visibility and driving safety	32.0	1.9	72.2	3.7	30.6	1.4	69.5	3.4	31.0	1.3	69.1	3.1
APEAL 6: Driving dynamics	64.1	4.1	64.5	2.1	59.1	4.2	62.2	1.5	60.5	4.3	61.8	1.3
APEAL 7: Fuel economy	7.4	0.5	15.9	0.4	7.4	0.6	15.4	0.3	7.2	0.4	15.3	0.4
APEAL 8: Interior	138.0	7.8	112.5	3.5	129.2	5.3	108.8	2.0	132.5	6.2	108.2	1.8
APEAL 9: Seats	104.8	10.0	113.5	5.5	96.5	6.2	109.8	4.0	110.2	15.8	108.5	2.0
APEAL 10: Storage and space	93.7	7.0	87.8	4.5	87.4	6.5	82.8	4.7	91.0	8.7	83.2	3.8
APEAL *total*	788.0	49.9	726.3	37.1	722.9	48.8	698.4	24.1	760.7	57.8	692.3	21.3
Num of automakers	15		25		3		10		3		5	
Num of models	27		118		4		30		4		19	

Notes: The year 2003 is the first year of the APEAL survey. The scores are at the model-by-year level, averaged over responses from approximately 100 car owners for each model-year. IQS scores measure the number of problems per 100 vehicles in the first three months of ownership across nine dimensions. APEAL scores are user satisfaction ratings on ten vehicle performance dimensions. Nonaffiliated domestic automakers include all private Chinese automakers and nonaffiliated SOEs that are not part of any JVs.

Table 2: Relative Quality Strength among JVs

	(1)	(2)	(3)	(4)	(5)	6
LeaderScore	-0.020***	-0.016***	-0.020***	-0.017***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
× SameFirm	0.312***	0.238***	0.302***	0.256***	0.301***	0.284***
	(0.023)	(0.018)	(0.022)	(0.018)	(0.021)	(0.019)
Observations	790,215	790,215	790,215	790,215	790,215	775,222
Partialling out:						
Firm FE	✓	✓				
Firm-year FE			✓			
Model FE				✓		
Model-year FE					✓	✓
Dimension-year FE	✓	✓	✓	✓	✓	
Dimension-Segment FE	✓	✓	✓	✓	✓	
Dimension-Segment-Year FE						✓

Notes: We randomly assign each JV model to be either a follower or a leader (with a 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 the set of fixed effects specified under each column is partialed out. Standard errors are clustered at the follower firm-dimension and leader firm-dimension level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table 3: Knowledge Spillover from JVs to Domestic Firms

	(1)	(2)	(3)	(4)	(5)	(6)
JVScore	-0.001	-0.008***	-0.006***	-0.009***	-0.007***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
× SameGroup	0.019	-0.001	0.004	0.017	0.006	0.016
	(0.017)	(0.017)	(0.013)	(0.018)	(0.016)	(0.010)
× SameSeg		0.043***	0.029***	0.040***	0.033***	-0.005***
		(0.008)	(0.006)	(0.008)	(0.006)	(0.001)
× SameGroup × SameSeg		0.108***	0.090***	0.116***	0.112***	0.087***
		(0.018)	(0.017)	(0.019)	(0.019)	(0.018)
Observations	738,948	738,948	738,948	738,948	738,948	717,500
Partialing out:						
Firm FE	✓	✓				
Firm-year FE			✓			
Model FE				✓		
Model-year FE					✓	✓
Dimension-year FE	✓	✓	✓	✓	✓	
Dimension-Segment FE	✓	✓	✓	✓	✓	
Dimension-Segment-Year 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 various fixed effects are partialed out. SameGroup equals 1 if the two models belong to a pair of affiliated automakers. SameSeg equals 1 if the two models belong to the same vehicle segment. Standard errors are clustered at the follower firm-dimension and leader firm-dimension level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table 4: Endogenous JV Formation

Founding Year	(1) All	(2) JV Formed Before 2000	(3) JV Formed After 2000
JVScore	-0.006***	-0.010***	0.001
	(0.002)	(0.004)	(0.002)
$\times$ SameGroup	0.097***	0.145***	
	(0.019)	(0.027)	
$\times$ SameGroup $\times$ JV Age ≤ 3			-0.232***
			(0.070)
$\times$ SameGroup $\times$ JV Age $\in [4,5]$			-0.110
			(0.081)
$\times$ SameGroup $\times$ JV Age $\in [6,10]$			-0.047
			(0.048)
$\times$ SameGroup $\times$ JV Age > 10			0.072***
			(0.030)
Observations	138,540	83,442	55,098
Partialling out:			
Model-Year FE	✓	✓	✓
Segment-Dimension-Year FE	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We focus on pairs of models produced by JVs and domestic automakers in the same segment, which explains the smaller number of observations than in Table 3. The unit of observation is a pair-year-quality dimension. Column (1) replicates our main result. Column (2) restricts the estimation to all pairs that involve models produced by JVs formed prior to 2000. In Column (3), we restrict the sample to pairs that involve models produced by JVs formed in 2001 or after, and estimate separate knowledge spillover effects for groups with different years of JV formation. Standard errors are clustered at the follower firm-dimension and leader firm-dimension level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table 5: Spillover through Ownership and Geographical Networks

JVScore interacted with	(1)	(2)
× SameGroup	0.097***	
	(0.019)	
× DiffGroup	-0.006***	
	(0.002)	
× SameGroup × SameProv		0.114***
		(0.028)
× SameGroup × DiffProv		0.080**
		(0.025)
× DiffGroup × SameProv		0.037
		(0.044)
× DiffGroup × DiffProv		-0.006***
		(0.002)
Observations	138,540	138,540
Partialing 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. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after dimension-year, model-year and dimension-segment fixed effects are partialed out. Interaction terms are dummy variables indicating whether the two models belong to the same affiliated group of automakers (*SameGroup*) or are located in the same province (*SameProv*). Standard errors are clustered at the follower firm-dimension and leader firm-dimension level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table 6: Mechanism of Knowledge Spillover: Worker Flow

	(1)	(2)	(3)	(4)
JVScore	-0.006***	-0.005	-0.006***	-0.006
	(0.001)	(0.003)	(0.002)	(0.005)
× SameGroup	0.103***	0.038*	0.027	0.044**
	(0.022)	(0.022)	(0.025)	(0.020)
× JVDomFlow		-0.001	-0.003	-0.011***
		(0.002)	(0.003)	(0.002)
× SameGroup × JVDomFlow		0.023***	0.023***	0.046***
		(0.006)	(0.006)	(0.008)
× DomJVFlow			0.006	
			(0.004)	
× SameGroup × DomJVFlow			0.000	
			(0.005)	
× JVDomFlow × HighTechShare				0.073***
				(0.016)
× SameGroup × JVDomFlow × HighTechShare				0.033
				(0.049)
Observations	138,540	138,540	138,540	80,621
Partialing out:				
Model-Year FE	✓	✓	✓	✓
Dimension-Segment-Year 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 dimension-year, model-year and dimension-segment fixed effects are partialed out. SameGroup is defined as in Table 3. JVDomFlow is a standardized measure of the number of workers who moved from a JV to a domestic automaker and vice versa for DomJVFlow. We identify six "HighTech" occupations directly related to the IQS quality measures. Those are feature designers, mechanical engineers, software engineers, procurement managers, and quality control and R&D professionals. HighTechShare is the z-score of the fraction of worker flow in one of these six occupations. Column (4) drops pairs with 0 worker flow (and hence an undefined HighTechShare). Standard errors are clustered at follower firm-dimension and leader firm-dimension level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table 7: Mechanism of Knowledge Spillover: Supplier Networks

	(1) All	(2) All	(3) Since 2012	(4) Since 2012
JVScore	-0.005***	-0.006***	-0.004***	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
× SameGroup	0.098***	0.084***	0.060***	0.033
	(0.021)	(0.025)	(0.020)	(0.020)
× SupplierOverlapRatio		0.016***		0.017***
		(0.001)		(0.003)
× SameGroup × SupplierOverlapRatio		-0.004		0.020
		(0.016)		(0.027)
Observations	128,354	128,354	71,364	71,364
Partialling out:				
Model-Year FE	✓	✓	✓	✓
Dimension-Segment-Year 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. Columns (1) and (2) contain pairs from all years from 2001 to 2014. Columns (3) and (4) restrict the sample to model pairs from 2012 to 2014. Both JV and domestic scores are residualized scores after dimension-year, model-year and dimension-segment fixed effects are partialed out. 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), standardized across all pairs of models. Standard errors are clustered at the follower firm-dimension and leader firm-dimension level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Appendices. For Online Publication Only

A Background of JV Formation in the Auto Industry

At the onset of the Chinese economic reform in 1978, Chinese leader Deng Xiaoping gave permission to the automobile industry to bring in foreign investment to develop the industry. Seeking foreign partners, China's First Ministry of Machinery, in charge of automobile production, invited major international automakers to visit China. GM was the first to send a delegation to China in October 1978. During the meeting with government officials, GM CEO Thomas Murphy put forward the idea of establishing a joint venture. Albeit a foreign concept to the Chinese hosts, the idea of using joint ventures to incentivize foreign automakers to provide technology was quickly reported to Deng Xiaoping. Deng supported the idea, which then became a longstanding industrial policy for the nation.[39]

The first JV was set up in 1983 between American Motors Corporation (AMC, later acquired by Chrysler) and Beijing Jeep Corporation Ltd., after four years of negotiations with the involvement of the highest levels of Chinese government. According to the first Chinese manager of the JV, the initiative to form this JV was approved by Deng Xiaoping and six vice premiers. The signing ceremony took place in the Great Hall of the People, signifying the critical role played by the central government. Present during the ceremony was the Vice Premier and Minister of the Ministry of Foreign Trade and Economic Cooperation, Chen Muhua, together with other high-level government officials. The first model produced by the joint venture was the Jeep Cherokee, a popular model in the US market and chosen by Chen on her first trip to visit AMC, instead of the obsolete BJ models initially agreed upon by both parties.[40]

The second joint venture was formed in 1984 between Volkswagen (50% equity), Shanghai Tractor Corporation (25% equity), Bank of China Shanghai Trust & Consulting Company (15%), and China Automotive Industry Corporation (10%). China's central government again played a major role in the JV formation. In hopes of securing a partnership with Daimler-Benz, the Minister of the First Ministry of Machinery (Zhou Zijian) led a delegation to visit Daimler-Benz's headquarters in November 1978. When Zhou arrived in Germany, he was surprised that Volkswagen (an unknown brand to China at the time)—not Benz—was the most popular brand on the street. He decided to visit Volkswagen's headquarters, some 500 km from the original destination. The surprise visit to Volkswagen led to the VW–Shanghai JV (later renamed VW–SAIC) six years later, again with a signing ceremony in the Great Hall of the People.[41]

These discussions suggest that the establishment of early JVs was primarily determined by political and idiosyncratic factors, with heavy involvement from high-level government officials. There is no evidence of concerns regarding the relative technological strengths of domestic automakers, which did not exist prior to the wave of JV formations.

[39] However, GM's board of directors vetoed the proposal to invest in China in 1978. Two decades later, in 1997, GM entered the Chinese market via a joint venture with Shanghai Automotive Industry Corporation.

[40] See http://finance.sina.com.cn/chanjing/sdbd/20130924/013316827769.shtml?from=wap.

[41] See http://auto.sohu.com/20110118/n278942357.shtml.

B 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 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 leader quality.

For illustration purposes, we assume that domestic models (followers) benefit from knowledge spillover from affiliated JVs (leaders) every year. This is not crucial to the quantification exercise and we present alternative results that do not rely on 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:

$$
\begin{aligned}
q_t^k &= \delta_t^k + \rho(Q_t^k - \delta_t^k) && \text{(B.1)}\\
&= \underbrace{(1-\rho)\bar{\delta}_t + \rho\bar{Q}_t}_{\text{follower model-year FE}} + \rho\mu_t^k + (1-\rho)\varepsilon_t^k && \text{(B.2)}
\end{aligned}
$$

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

$$
\xi_t^k = \rho\mu_t^k + (1-\rho)\varepsilon_t^k \qquad \text{(B.3)}
$$

This expression maps to our pairwise empirical framework. Intuitively, knowledge spillover translates into similar quality strengths between the leader and the follower, $\rho\mu_t^k$. The intrinsic relative quality strength of follower in the absence of spillover, ε_t^k, 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 (B.1) to back out the extent of knowledge spillover between each leader-follower pair in each year. For domestic models with multiple leaders, we calculate average spillover from the set of leaders. The reduction in quality of a follower when *quid pro quo* was lifted in 2007 is the sum of spillover between 2007 and year t.

C Effects of Knowledge Spillover on Vehicle Sales and Profits

We estimate an equilibrium model of demand and supply in the tradition of Berry, Levinsohn, and Pakes (1995) to quantify the effects of knowledge spillover on vehicle sales and firm profits. Specifically, we extend the model in Barwick, Cao, and Li (2020) by allowing both demand and cost of production to depend on vehicle quality measured by IQS. The model would allow us to simulate counterfactual equilibrium outcomes (e.g., prices and sales) when we lift *quid pro quo*.

C.1 A Structural Model of the Automobile Market

Our primary data covers provincial-level annual sales and vehicle attributes by model between 2009 and 2014. We define a province-year as a market. In each market, each household chooses from J_{mt} models to maximize its utility. We define the indirect utility of household i buying product j in market m and year t as:

$$\bar{u}_{ijmt} = \gamma q_{j,t-1} - \alpha_{imt}\mathrm{p}_{jt} + \sum_{k=1}^{K} \mathrm{X}_{jkt}\tilde{\beta}_{ikmt} + \xi_{jmt} + \varepsilon_{ijmt}.$$

Utility depends on past vehicle quality $q_{j,t-1}$, price p_{jt}, vehicle attributes X_{jkt}, unobserved demand shock ξ_{jmt}, and an idiosyncratic match value ε_{ijmt} that follows the type I extreme value distribution.

We measure quality using the IQS score, for which a higher score indicates lower quality. We assume that it takes one year for consumers to observe quality (hence the lagged $q_{j,t-1}$). Past quality affects brand reputation, which influences demand. Household i's marginal utility from a dollar, α_{imt}, is defined as

$$\alpha_{imt} = e^{\alpha_0 + \alpha_1 ln(y_{imt}) + \sigma_p \nu_{imt}},$$

where y_{imt} is the annual income of household i in province m in year t. Parameter α_1 captures how the marginal utility from a dollar changes as the household gets richer. The second component $\sigma_p \nu_{imt}$ is a random shock representing idiosyncratic factors that influence price elasticity, such as inheritance and assets accumulated in the past. We assume that all households dislike higher prices, as the exponential form guarantees.

X_{jt} is a vector of vehicle attributes, including the log of fuel cost, vehicle size, engine size, and a dummy for automatic transmission. It also includes brand fixed effects, segment by market fixed effects, and year fixed effects. We allow a random coefficient on the constant term to capture heterogeneity in households' outside options. The last element, ξ_{jmt}, captures all unobserved product attributes or transient demand shocks.

On the supply side, we follow the literature and assume that all firms set prices at the national level to maximize profits under Bertrand-Nash competition. The marginal cost of product j in year t depends on vehicle quality, other vehicle attributes, and a random cost shock:

$$\mathrm{mc}_{jt} = q_{jt}\phi + W_{jt}\theta + \omega_{jt}, \tag{C.4}$$

Parameter ϕ measures the marginal cost of quality improvement, such as additional costs incurred in sourcing better parts and components. Firms also incur fixed costs in quality improvement, such as in getting technology breakthroughs or access to exclusive, high-quality suppliers. We do not model the fixed costs explicitly. The gains in variable profits from quality improvement provide an upper bound on the fixed cost.

C.2 Identification and Estimation

To identify households' marginal utility from a dollar, we need to address both the endogeneity of prices and the fact that market shares need to be "instrumented" in a non-linear model (Berry and Haile, 2014). To this end, we leverage three sets of instruments: the "BLP instruments", consumption tax rates, and panel variations in household income. In addition, we identify the preference heterogeneity across different income groups using a representative survey of new vehicle buyers conducted by Ford, which shows the fractions of households in different income brackets among all new-car buyers, and among buyers in each vehicle segment. Our identification strategy closely follows Barwick, Cao, and Li (2020), where we provide additional details on identification and estimation.

To identify preferences for quality γ, we assume that lagged vehicle quality $q_{j,t-1}$ is uncorrelated with unobserved product attributes ξ_{jmt} after controlling for brand fixed effects and year fixed effects. We consider this assumption reasonable because past quality was decided before transient demand shocks are realized, conditioning on brand and year fixed effects. With these fixed effects, we identify consumers' preferences for quality from two sources of variations: cross-sectional variations in quality between different products of the same brand and the changes in quality of each product over time.

C.3 Results

Table C.1 shows results from demand estimation. In column (1), where we do not control for brand fixed effects, the IQS coefficient also picks up the effects of persistent brand reputation correlated with car quality. When we control for brand fixed effects in column (2), we find a smaller but still sizeable effect of past car quality on demand. The estimate implies that the elasticity of demand to IQS is about -0.60, and an average car buyer is willing to pay around 100 yuan for one unit improvement in IQS (i.e., one fewer defect).

Coefficients on all other main vehicle attributes are intuitively signed and statistically significant. All else equal, consumers prefer more fuel-efficient, larger, and more powerful vehicles, as well as vehicles with automatic transmission. Wealthier households are less price sensitive, and there is significant heterogeneity in the access to the outside option among consumers.

Table C.2 shows results from the supply side. Coefficient estimates on all key vehicle attributes are intuitively signed. Improving IQS by one unit increases the marginal cost by around 38 yuan. Combined with the demand-side estimates, our results imply that improving IQS by one unit on average increases variable profit by around 62 yuan per car.

With the model parameters estimated for both the demand and supply sides, we simulate equilibrium market outcomes allowing vehicle prices to adjust after lifting *quid pro quo*, under different scenarios of learning and hence quality improvement. Table C.3 presents the impacts on sales and profit by different types of automakers. When we assume learning is static (that is, the benefit that domestic affiliated firms experience in a given year is proportional to the gap between this year's JV quality and domestic quality in 2007), we find that lifting *qud pro quo* in 2007 would reduce sales of affiliated domestic models in 2014 by 0.9%. Sales of nonaffiliated domestic and JV models would increase by less than 0.1% due to reduced competition. When we assume that cumulative learning, sales of affiliated domestic models would fall by 3.9%. As shown in Table C.3, impacts on firm profits are similar given the small changes of vehicle prices.

Overall, lifting *quid pro quo* in 2007 would have reduced sales of affiliated domestic models in 2014 by between 0.9% and 3.9%, and sales of all domestic models by between 0.5% and 2.0%. Total variable profits by domestic automakers would fall by between 330 and 1,120 million yuan ($50 - $165 million).

Table C.1: Results from the Demand Model

	(1)		(2)	
	Est.	S.E.	Est.	S.E
Linear Parameters				
IQS (prior year)	-0.70***	0.04	-0.39***	0.05
log(Fuel cost)	-2.34***	0.25	-0.81***	0.24
log(Size)	10.41***	0.37	19.92***	0.48
log(Displacement)	1.32***	0.19	3.98***	0.22
Auto Transmission	1.21***	0.03	1.50***	0.04
Nonlinear Parameters				
Price coeff α_0	-5.39***	0.87	-2.64***	0.24
Income parameter, α_1	-1.30***	0.07	0.76***	0.05
RC Constant, σ_1	7.68***	0.51	7.96***	0.27
RC price, σ_p	0.22***	0.06	0.00	0.03
Fixed Effects:				
Year FE	✓		✓	
Segment-market FE	✓		✓	
Firm Type FE	✓			
Brand FE			✓	

Notes: The table presents results from a random coefficient multinomial logit model (à la BLP). The linear parameters capture the average preference across households while nonlinear parameters capture preference heterogeneity. We use three sets of IVs for identification: the BLP instruments, consumption tax rates which varies by engine size, and panel variations in household income. The first-stage F-statistic is 713.2 for both columns. The standard errors are clustered at the firm level. * p < 0.1, ** p<0.05, *** p<0.01.

Table C.2: Results from the Supply Side

	(1)		(2)	
	Est.	S.E.	Est.	S.E
IQS (Current)	0.046***	0.005	0.037***	0.005
log (Fuel cost)	-27.53***	5.04	-31.65***	5.53
log (Size)	145.77***	2.74	168.89***	2.70
log (Displacement)	86.48***	3.73	96.56***	3.71
Auto Transmission	6.14***	0.51	7.74***	0.49
Fixed Effects:				
Year FE	✓		✓	
Segment-market FE	✓		✓	
Firm Type FE	✓			
Brand FE			✓	

Note: The table presents parameter estimates for the marginal cost of production. The dependent variable is the marginal cost ('000 yuan) of each model. The standard errors are clustered at the firm level. * $p < 0.1$, ** $p<0.05$, *** $p<0.01$.

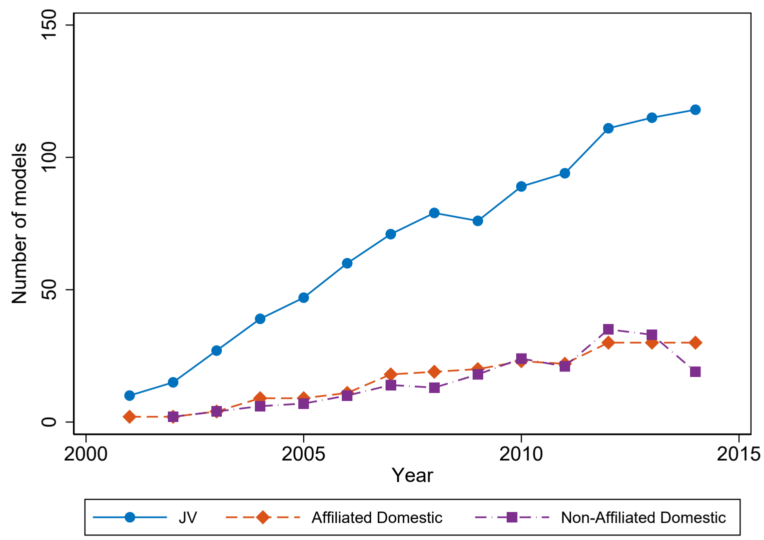
Table C.3: Equilibrium Impacts of Knowledge Spillover on Sales and Profits

	Current	CF, one-shot	% change	CF, cumulative	% change
Sales (milion), aff domestic	1.79	1.77	-0.86%	1.74	-3.90%
Sales (milion), nonaff domestic	1.68	1.68	0.06%	1.68	0.20%
Sales (milion), JV	10.78	10.79	0.04%	10.80	0.15%
Profits (bil yuan), aff domestic	32.33	32.00	-1.02%	31.21	-3.49%

Notes: This table shows the effects of lifting *quid pro quo* in 2007 on car sales and profits in 2014. "Aff domestic" denote domestic automakers that form JVs with foreign automakers. Sales are measured in million units. Profits are measured in billion yuan.

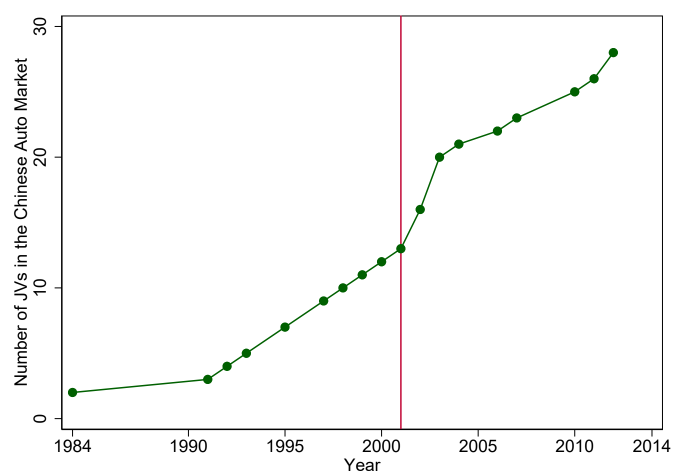
D Figures and Tables

Figure D.1: Number of Models by Ownership Over Time



Notes: Thig figure shows the the number models of each firm type covered by the J.D. Power surveys in each year. 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. nonaffiliated domestic automakers are those automakers that do not have joint ventures.

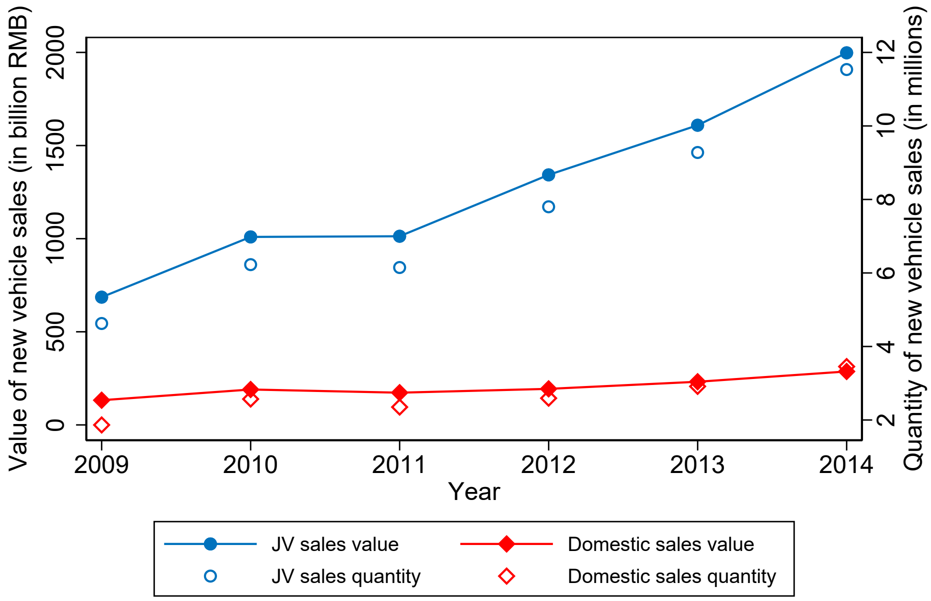
Figure D.2: Entry of International Joint Ventures



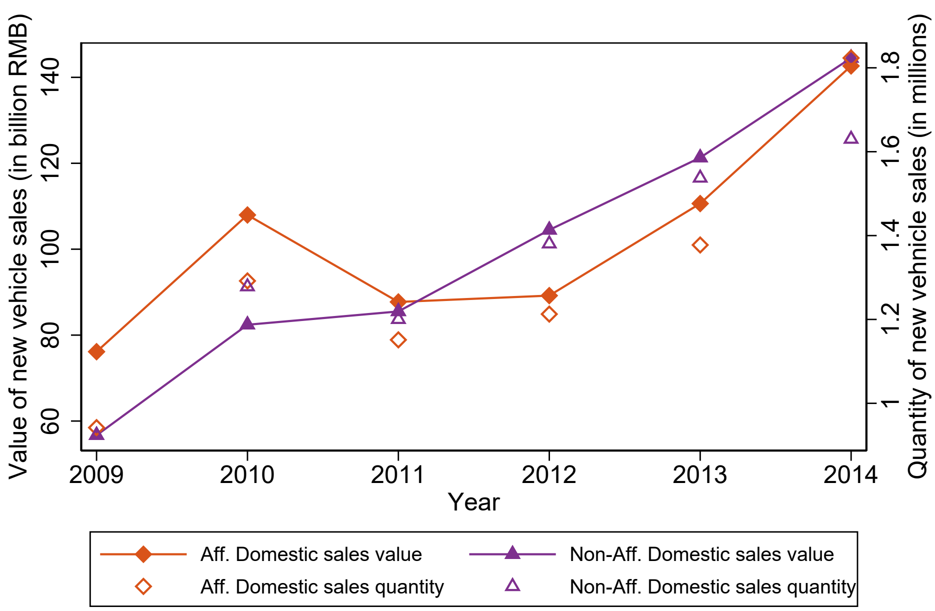
Notes: The figure plots the number of JVs in the Chinese auto market over time. Significant entries include: (1) 1984-1994: VW-Shanghai, VW-FAW, PSA-Dongfeng, Suzuki-Changan; (2) 1994-2000: GM-Shanghai, Honda-Guangzhou, Toyota-FAW, Suzuki-Changhe; (3) post 2000: Ford-Changan, Nissan-Dongfeng, Hyundai-Beijing,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

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

Panel A. Performance of JVs and Domestic automakers

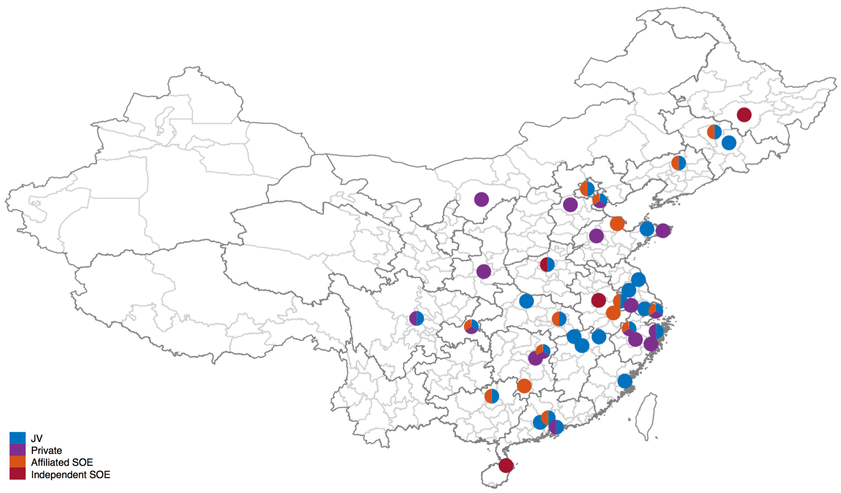


Panel B. Performance among Domestic automakers



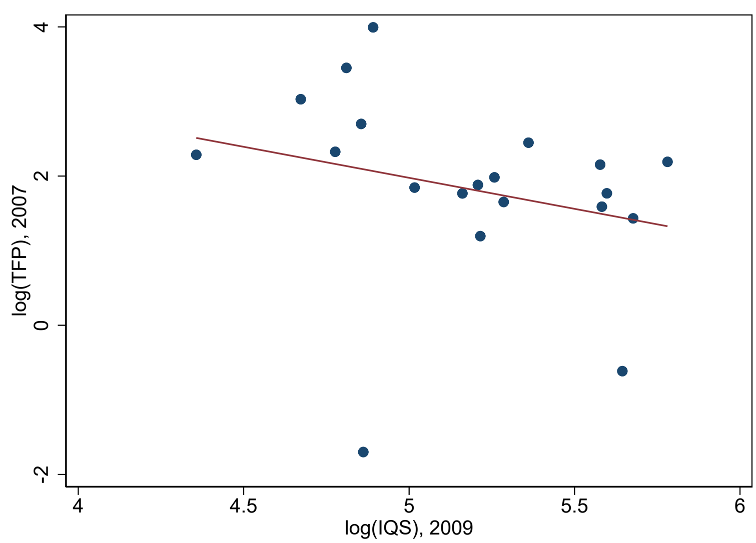
Notes: Sales value and quantity are calculated using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year, and does not include imported models, which account for around 3% of total sales.

Figure D.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 D.5: Relationship of Firm TFP and IQS



Notes: This figure shows a log-log binscatter plot of firm-level TFP in 2007 and firm-average IQS in 2009. Sample consists of 23 firms.

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

Joint Venture	Foreign Partner	Chinese Partner	2014 Sales	2014 Shares
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 D.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 D.3: Knowledge Spillover: Fixed Effect Models

	(1)	(2)	(3)	(4)	(5)	(6)
JVScore	-0.001	-0.007***	-0.006***	-0.007***	-0.008***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
× SameGroup	0.024	0.004	0.022	0.017	0.021	0.033
	(0.018)	(0.017)	(0.019)	(0.017)	(0.024)	(0.021)
× SameSeg		0.035***	0.022***	0.031***	0.032***	-0.008***
		(0.008)	(0.005)	(0.007)	(0.006)	(0.001)
× SameGroup × SameSeg		0.116***	0.093***	0.113***	0.145***	0.127***
		(0.024)	(0.019)	(0.022)	(0.026)	(0.022)
Observations	739,001	739,001	739,001	739,001	739,001	738,695
Partialling out:						
Firm FE	✓	✓				
Firm-year FE			✓			
Model FE				✓		
Model-Year FE					✓	✓
Dimension-Year FE	✓	✓	✓	✓	✓	
Dimension-Segment FE	✓	✓	✓	✓	✓	
Dimension-Segment-Year 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 D.4: Knowledge Spillover: Alternative Clustering of Standard Errors

	(1)	(2)	(3)	(4)
JVScore	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)
JVScoreXSameGroup	0.016	0.016	0.016	0.016
	(0.010)	(0.022)	(0.028)	(0.015)
JVScoreXSameSeg	-0.005***	-0.005	-0.005***	-0.005***
	(0.001)	(0.006)	(0.001)	(0.001)
JVScoreXSameSegSameGroup	0.087***	0.087***	0.087*	0.087**
	(0.018)	(0.027)	(0.051)	(0.036)
Observations	717,500	717,500	717,500	717,500
Clusters:				
Domestic Firm				✓
JV Firm				✓
Domestic Firm - Segment	✓			
JV Firm - Segment	✓			
Domestic-JV Firm Pair				
Domestic-JV Firm Pair - Segment		✓	✓	
Domestic Firm - Year			✓	
JV Firm - Year			✓	

Note: This table replicates Column (6) in Table 3 under six alternative clustering of the standard errors. In all columns, we first partial out model-year fixed effects and dimension-segment-year fixed effects. Columns (1) clusters the standard error two-way at domestic firm-quality dimension and JV firm - quality dimension levels. Columns (2) clusters the standard error at domestic-JV firm pair-quality dimension level. Columns (3) in the top panel clusters 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 (4) clusters the standard error two-way at domestic firm and JV firm levels. Columns (5) clusters the standard error at domestic-JV firm pair level. Finally, Columns (6) clusters the standard error three-way at domestic-JV firm pair, domestic firm-year and JV firm-year levels.

Table D.5: Dynamic Spillover Effects

	(1) Lag 0	(2) Lag 1	(3) Lag 2	(4) Lag 3
JVScore	-0.002	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
JVScoreXSameGroup	0.033**	-0.005	-0.006	-0.016
	(0.014)	(0.013)	(0.014)	(0.012)
JVScoreXSameSeg	-0.006***	-0.005**	-0.004***	-0.001***
	(0.001)	(0.002)	(0.001)	(0.000)
JVScoreXSameGroupSeg	0.094***	0.080**	0.069**	0.020
	(0.022)	(0.032)	(0.028)	(0.021)
Observations	445,794	418,109	379,337	334,424
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 at least four years during the 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 and 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 D.6: 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 vehicle ownership survey. Each observation is a pair of models in a year. The dependent variable is the log number of times that a pair is listed as the top two choices by households in the survey data. Attribute controls include differences in price, car size, and engine power. SameGroup and SameSeg are defined in Table 3. SameOwnershipType takes value 1 if both are JV models or both are domestic models. In Columns (2) and (3), the omitted group includes pairs not produced by affiliated automakers, not in the same segment, and not produced by firms of the same ownership type. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.