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

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**Abstract**

While there is a vast body of research on the benefits of FDI in developing countries, whether and how the *form* of FDI matters have received limited attention. In this paper, we study the impact of FDI via *quid pro quo* (technology for market access) on facilitating knowledge spillover and quality upgrading. Our context is the Chinese automobile industry, where foreign firms are required to set up joint ventures with domestic firms in return for market access. Using a unique dataset of detailed quality measures of vehicle performance, we show that affiliated joint ventures and domestic firms share a greater similarity in quality strength compared to non-affiliated pairs. The results suggest that *quid pro quo* spurs additional knowledge spillover to affiliated domestic firms, in addition to any industry-wide spillover as a result of the presence of foreign firms. The identification relies on *within*-product quality variation across different dimensions, and the results are robust to a variety of specifications. We rule out endogenous joint venture network formation, overlapping customer base, or direct technology transfer via market transactions as alternative explanations. Analyses leveraging additional micro datasets on part suppliers and worker flows among firms demonstrate that supplier network and labor mobility are important channels in mediating knowledge spillover. On the other hand, while ownership affiliation facilitates learning, such a requirement is not a prerequisite for knowledge spillover. Counterfactual exercises show that the role of *quid pro quo* is modest in explaining the overall quality improvement experienced by domestic firms.

Keywords: 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 various international organizations (UNCTAD, 2018; World Bank, 2018). At the same time, countries including China, India, and Brazil have been imposing considerable restrictions on foreign direct investment (FDI) in certain sectors for strategic considerations. One such policy is "*quid pro quo*" (technology for market access), which requires multinational firms to form joint ventures (JVs) with domestic firms, often with a significant cap on foreign equity, in return for gaining access to the large domestic market of the host country (Karabay, 2010).[1] 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. Concern over *quid pro quo* was a key stated justification behind Trump administration's decision to impose tariffs on $50 billion of Chinese imports in 2018.[2]

Despite the controversy surrounding *quid pro quo*, little is known about its benefits to the host country, compared to unrestricted FDI. The vast existing literature on FDI has paid relatively little attention to whether and how the *form* of FDI matters (see Keller 2004, 2010 for extensive reviews). In this paper, we attempt to fill the knowledge gap by examining the importance and necessity of the *quid pro quo* requirement in facilitating knowledge spillover from foreign to domestic firms in developing countries. Different from previous analysis that mostly focus on firm-level TFP as the outcome measure, we zoom into one industry and exploit novel and comprehensive product-level quality measures that embody firms' fundamental technological capabilities and underlie TFP growth.

Our context is the Chinese automobile industry, which presents an ideal setting for this research agenda for the following three reasons. First, *quid pro quo* has been a longstanding major industrial policy in China and was first implemented in the auto industry. Second, China has the largest automobile industry in the world where all major multinational automakers compete. Third, the automobile industry is a classical industry for studying knowledge spillover, given the multitude of technologies embodied in the final products, including propulsion, electronics, safety, fuel efficiency, emission control, materials, and most recently AI (Knittel, 2011; Aghion et al., 2016). In recent years, Chinese domestic automakers have developed high-quality indigenous brands, potentially benefiting from knowledge spillover from foreign firms.

We aim to answer the following questions. Has the ownership affiliation stipulated under the *quid*

[1] China keeps a 50% foreign ownership cap in 38 "restricted access" industries. Vietnam has a 49% foreign ownership cap for all publicly listed companies. 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.

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

*pro quo* policy been effective in inducing knowledge spillover from foreign automakers to domestic automakers? If so, to what extent and what are the underlying mechanisms that mediate the knowledge flow? What would happen if *quid pro quo* were lifted? To answer these questions, we have compiled the most comprehensive data on this industry. Our primary dataset consists of quality measures over multiple dimensions for all major car models produced in China from 2009 to 2014.[3] We supplement the rich and granular quality data with information on firm ownership network, household vehicle ownership surveys, production location for each car model, parts and components suppliers at the model level, worker flows among firms, and patent transfers between JVs and domestic firms.

Using the newly assembled dataset, we first document descriptive patterns of quality catch-up of Chinese domestic automakers. Then we propose a novel identification strategy for detecting knowledge spillover induced by *quid pro quo*, exploiting rich within-product variation across different quality dimensions. We further examine potential underlying mechanisms. Lastly, we quantify the impact of *quid pro quo* on domestic quality upgrading and discuss the policy implications of removing such ownership restrictions.

The quality of cars produced by Chinese domestic automakers exhibits an impressive record of improvement, with the malfunction rates cut in half in less than a decade. The quality gap between models produced by domestic firms and JVs has greatly narrowed: the malfunction rate for domestic firms was twice as high as that for JVs in 2009. By 2014, the gap has shrunk to 33%.

While many factors may explain the overall quality upgrading of the industry, including intense competition and rising household income, we focus on the role of *quid pro quo*. A key feature of *quid pro quo* is the joint ownership requirement, which creates a set of domestic firms that are affiliated with foreign multinationals through the JVs. These domestic firms are presumably the primary beneficiaries of the policy, with better access to foreign technology. Hence, to isolate knowledge spillover as a result of ownership affiliation under *quid pro quo* from the general spillover to the domestic industry due to the presence of foreign firms (for example, through training skilled workforce and facilitating the upgrading of the upstream industry), we look for *differential* spillover from JVs to affiliated domestic firms, relative to that received by non-affiliated domestic firms.

Specifically, we construct quality strength for each car model, foreign and domestic, in different quality dimensions (e.g., fuel efficiency) and look for similarity in strength between "leaders" (JVs) and "followers" (affiliated and non-affiliated domestic firms). In doing so, we control for a rich set of vehicle segment, quality category, and year interacted fixed effects. Importantly, we include model-year fixed effects to capture the overall time-varying model quality and exploit *within-model* relative strength (or weaknesses) across different quality dimensions. One example of such variation is whether

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

domestic firms affiliated with German automakers produce models that have relatively better engines and firms affiliated with Japanese automakers are more fuel efficient. This demanding specification and the granularity of our data set us apart from other studies in the literature and allow us to better control for industry-wide, firm-specific, or model-level confounding factors that also affect quality.

We find that when a JV model scores one standard deviation higher in a quality dimension, indigenous models by its domestic partner in the same vehicle segment score 0.138 standard deviation higher in the same dimension, relative to non-affiliated models. This pattern of shared quality strength is robust to a variety of specifications, and is indicative of knowledge spillover from JVs to affiliated firms.

We examine a number of confounding factors that may also lead to shared quality strength between affiliated partners. The first concern is the endogenous JV formation where foreign firms target domestic firms with similar quality strength as partners. The rich set of firm and model level fixed effects help to mitigate this concern. To investigate it further, we limit our sample to JVs formed prior to 2000. These JVs were established in a period that predates our sample by at least a decade with few indigenous brands. The pattern of shared quality persists for this sub-sample. Our results also survive a more demanding specification that directly controls for any initial correlation in quality measures using model by quality category fixed effects and only exploits temporal variation for identification. The second concern is that both JVs and their affiliated firms might target the same set of consumers and hence design products similarly. However, analyses using the household vehicle ownership surveys indicate that models by JVs and affiliated domestic partners are not considered as close substitutes by most car buyers. Lastly, the observed patterns of knowledge spillover might be driven by market transactions, such as patent licensing and assignment. Using records from the universe of patent applications and transfers, we find *no* patent transfer activity from JVs to affiliated SOEs during our sample period.

Having demonstrated the presence of knowledge spillover from JVs to their affiliated firms, we consider two potential mechanisms, worker flows and supplier network, both of which have been documented in the literature. As carriers of technology know-how, workers move across firms and serve as a conduit of knowledge spillover, especially skilled workers.[4] We construct worker flows between each pair of JV and domestic firms using data from LinkedIn (China), whose number of users in the auto industry closely mimics local volume of auto production. We find higher rates of worker flows between affiliated pairs than non-affiliated pairs. The flows from JVs to affiliated domestic firms, rather than the reverse, are associated with knowledge spillover. In addition, high-tech workers (engineers and designers) appear more relevant for knowledge spillover, though the estimate is insignificant. These findings corroborate

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

well results in the existing literature and are consistent with anecdotal evidence that domestic firms benefit from recruiting talents from foreign firms with advanced technology. Worker flows that domestic firms receive from affiliated JVs explain 58% of knowledge spillover via ownership affiliation.

The second mechanism that we investigate is motivated by the observation that high-quality parts and components directly affect the overall performance of the downstream product. JVs' high quality standards for their suppliers in the host country often enhance the performance of the latter. If the affiliated domestic firms source from the same set of part suppliers that serve JVs, they could directly benefit from the 'shared supplier spillover'.[5] Using the supplier network data from MarkLines, we calculate the number of common part suppliers shard by pairs of JV and domestic models. JVs and affiliated domestic firms have a significantly greater supplier overlap, which contributes to 32% of knowledge spillover via ownership affiliation.

Finally, we turn to the policy counterfactual of what would happen to domestic firms' quality if *quid pro quo* were lifted. We perform three reduced-form analyses and one quantification exercise. First, we examine whether ownership affiliation stipulated by the *quid pro quo* policy is a prerequisite for knowledge spillover. By exploiting partial overlaps in ownership and geographic networks, we show while spillover is the strongest between affiliated JV-domestic pairs in the same city, there is also sizeable knowledge spillover from JVs to non-affiliated firms located in the same city. This result suggests that ownership affiliation, as required by *quid pro quo*, is not a necessary condition for knowledge spillover.

A skeptical view of the above finding, however, is that spillover to non-affiliated firms could only happen with some form of *quid pro quo* in place, and that affiliated domestic partners are crucial 'conduits' for knowledge to flow from foreign firms to domestic firms. Once a firm becomes wholly foreign-owned, it can manage to silo its know-how, resulting in fundamentally different spillover patterns. To address this issue, we limit our analysis to a subset of cities that host a JV plant and non-affiliated plants, but none of the affiliated domestic plants. The economically large and statistically significant spillover between models by JVs and non-affiliated firms suggests that the presence of affiliated domestic firms is not a necessary conduit for knowledge to flow from foreign firms to domestic ones. We further exploit the fact that the upstream parts and components sector has never been subject to *quid pro quo*, with both wholly foreign-owned firms as well as JVs. By mapping the quality measures of car components to part suppliers using the supplier network information and replicating our analysis in the upstream industry, we find no evidence that the spillover from wholly foreign-owned firms is less than that from JVs.

We end with a quantification exercise where we shut down *quid pro quo* and simulate the quality evolution of domestic models. Lifting *quid pro quo* in 2009 would have reduced the quality improvement

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

experienced by domestic models from 2009 to 2014 by 5.7% to 16.5%. The results suggest that *quid pro quo* has a modest effect on technology progress in our setting, partly because knowledge spillover and learning could happen through other channels even if foreign firms were to operate as wholly-owned companies. Amid recent trade tensions with the US, the Chinese government has pledged to further open up its automobile market through lifting the foreign ownership requirement by 2022. Our findings suggest that doing so would not significantly hinder the upgrading of the domestic industry.

It is important to acknowledge several caveats of our analyses. First, the data coverage prevents us from evaluating the historical efficacy of *quid pro quo*, i.e., what would have happened if China did not have the policy from the beginning. It is conceivable that market-for-technology policies are more effective as an infant industry takes off and less effective when the industry matures. Nonetheless, it is worth pointing out that prior to 2000, there were few indigenous brands and the majority of JV's manufacturing activity was made up of "knock-down kit" assembly, thus limiting the scope of knowledge spillover. Second, our study focuses on spillover to domestic firms *conditioning on* the existing set of products and technologies introduced by foreign firms. Future work is needed to examine foreign firms' incentives to introduce product and technology in light of global knowledge spillover (Buera and Oberfield, 2016; Bilir and Morales, 2016).

Our study contributes to several strands of literature. While there is an extensive empirical literature on FDI and technology spillover,[6] whether and how the form of FDI affects quality upgrading in the host country have received little attention (Blomström and Sjöholm, 1999; Javorcik, 2004; Javorcik and Spatareanu, 2008). Our study shows that while *quid pro quo* helps, its role in facilitating knowledge spillover and promoting quality improvement among domestic firms in our setting is modest relative to unrestricted FDI.

Second, most of the FDI literature relies on industry-level variation in FDI presence or intensity to identify the impact on the host country (e.g., Aitken and Harrison (1999); Javorcik (2004); Keller and Yeaple (2009)). However, entry of foreign firms could be affected 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. In addition, many studies focus on TFP improvement as the key outcome variable, which embeds both the positive spillover effect and the negative competition effect. We contribute to the literature by using direct measures of quality at the product level, which enable us to look inside the black box of TFP improvement. Our identification relies on within-product (i.e., vehicle model) quality strength, while controlling for industry-wide, firm-level and product-specific unobserved attributes that might be correlated with joint-venture formation. In addition, we analyze

[6]Papers in this literature include Haddad and Harrison (1993); Haskel, Pereira, and Slaughter (2007),Blalock and Gertler (2008b); Kosova (2010); Havranek and Irsova (2011); Gorodnichenko, Svejnar, and Terrell (2014), and Lu, Tao, and Zhu (2017). Keller (2004, 2010) provide two comprehensive reviews on the findings and highlight the measurement and identification challenges in the literature.

the role of worker flows and supplier networks, two important pathways of knowledge spillover.

Third, our paper relates to the growing body of work in trade and development that aims at understanding the importance of technology innovation and quality upgrading in economic growth, especially in developing countries (e.g., Khandelwal (2010); Goldberg et al. (2010); Buera and Oberfield (2016); Atkin, Khandelwal, and Osman (2017); Bastos, Silva, and Verhoogen (2018); Fieler, Eslava, and Xu (2018)). The existing literature mostly focuses on indirect measures of technology and quality improvement, such as market shares and prices (Khandelwal, 2010), because quality is rarely observed in standard firm surveys. Our study adds to the nascent literature leveraging detailed quality measures for specific industries (Atkin, Khandelwal, and Osman, 2017) to examine the impact of trade on innovation and product quality.

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

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

## 2 Background and Data

### 2.1 The Chinese Auto Industry and *Quid Pro Quo*

When China started its reform and open-up policy in 1978, China's automobile manufacturing was concentrated in heavy trucks and buses with virtually no production capacity of passenger cars. To develop its domestic passenger car sector, the Chinese government allowed international automakers to enter but required them to partner with domestic automakers to set up a production facility. In forming joint ventures (JVs), foreign automakers offer know-how and product lines as equity, which is capped at 50%, while domestic automakers provide manufacturing facility and labor.[7] *Quid pro quo* is implemented in many industries that are considered strategically important, from advanced manufacturing such as

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

aircraft and shipbuilding to service sectors such as banking and higher education. There are at least two rationales for the policy. The first is to protect young and small domestic producers in nascent industries (i.e., the infant industry argument). The second is to enhance domestic technical capabilities and allow domestic firms to learn from their foreign partners.

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

Prior to 2000, most of the affiliated domestic firms relied on the JVs for production of passenger vehicles.[8] There were few indigenous brands in the country, as shown in Appendix Figure B.1. In 2004, the central government announced an explicit goal of developing domestic automotive technology and promoting indigenous brands through supporting the establishment of R&D facilities using tax incentives. The 2009 Automotive Adjustment and Revitalization Plan encourages mergers and reorganization of automobile firms and calls for the creation of new indigenous brands, both for export and domestic sales. Under these government policies, affiliated domestic automakers started to launch their own brands of passenger vehicles. For example, SAIC launched Roewe, and FAW launched its first indigenous brand, Besturn, both in 2006. Dongfeng built its own assembly plants in 2007 and introduced its first indigenous model in 2009. By 2014, the affiliated domestic automakers have caught up with non-affiliated domestic firms in product offering.

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

The industry has witnessed unprecedented growth after China entered the WTO in 2001. Sales of

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

new passenger vehicles increased from 0.85 million units in 2001 to 24.7 million units in 2017, surpassing the US in 2009 to become the world's largest market.[9] In 2017, China alone accounts for more than 33% of the global auto production and sales. The industry is highly competitive and consists of 48 firms with production exceeding 10,000 units in 2014. The number of JVs has also steadily increased (Appendix Figure B.2): by 2009, most of the major international automakers have launched JVs in China. Appendix Table B.1 lists the JVs and their sales and market shares in 2014. While the JVs have been dominating the industry, sales of domestic firms have also been growing over the past decade (Figure B.3). This is especially true in the SUV segment, where the market shares by domestic firms grew from 27% to 36% between 2009 and 2014.

Under the terms of WTO, explicit technology transfer requirements for market access are not permitted. Hence *quid pro quo* in China has been mostly carried out implicitly via ownership restrictions on joint ventures to facilitate technology transfer from the foreign firms. It is considered by some countries as part of China's broad industrial policy that creates unfair advantages for its domestic companies. Because of the emphasis on technology transfer, this policy is criticized as state-sponsored efforts to systematically pry technology from foreign companies. According to the 2018 China Business Climate Survey Report conducted by the American Chamber of Commerce, 21% of 434 companies surveyed in China faced pressure to transfer technology. Such pressure is most often felt in strategically important industries such as aerospace (44%) and chemicals (41%).[10]

Amid recent trade tensions with the US, the Chinese government pledged to further open up its automobile market through lifting the foreign ownership cap by 2022, representing a major shift from the *quid pro quo* policy in place for around four decades. This effectively allows foreign automakers to have solely-owned production facilities in China. Following the pledge, BMW and its domestic partner Brilliance reached an agreement where BMW pays Brilliance $4.1 billion for a 25% stake in the joint venture to increase BMW's ownership share to 75% by 2022.[11] Many have speculated that this could have profound impact not only on the Chinese market but also on the global industry. Understanding the role played by ownership affiliation serves as a crucial step in understanding the implications of removing *quid pro quo*.

## 2.2 Data

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

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

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

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

**Vehicle quality measures** Quality measures come from the annual Initial Quality Study (IQS) and Automotive Performance, Execution and Layout Study (APEAL) that are conducted by JD Power between 2009 and 2014. Between April and June each year, JD power recruits subjects who have purchased a vehicle for less than a year in over 50 cities in China, and surveys their user experience during the first six months of vehicle ownership. The survey covers major passenger vehicle models in China, accounting for over 9% of market shares in terms of sales in 2014. The total number of survey correspondents in 2014 is 18,884, or around 110 car owners per model. The IQS study reports the number of problems experienced per 100 vehicles during the first 90 days of ownership. The survey asks 227 questions covering a complete spectrum of vehicle functionalities, which are aggregated to nine quality dimensions: exterior problems, driving experience, feature/control/displays, audio/entertainment/navigation, seat problems, HVAC problems, interior problem, and engine and transmission.[12] Industry experts believe that initial quality is an excellent predictor of long-term reliability, which has a significant impact on owner satisfaction and brand loyalty.

The APEAL study elicits user satisfaction ratings over 100 vehicle quality attributes, which are grouped to ten performance dimensions: interior, exterior, storage and space, audio/entertainment/navigation, seats, heating/ventilation/air-conditioning, driving dynamics, engine/transmission, visibility and driving safety, and fuel economy.[13]

Figure 2 presents the residualized figures on vehicle prices and the two quality measures. Panel A plots prices against IQS, with the left figure controlling for vehicle size and horsepower/weight (proxy for acceleration) and the right figure further controlling for year fixed effects, segment fixed effects, and ownership type fixed effects.[14] Panel B shows the relationship between prices and APEAL with the same controls as in Panel A. The remarkably tight correlations between price and IQS/APEAL provide strong evidence that IQS and APEAL are reliable measures of vehicle quality, with high quality car models consistently commanding high prices.

**Worker flow** To examine worker mobility, especially that among technicians, we collect data on the employment history for all past and current employees in the Chinese auto industry who are registered on LinkedIn (China). The data contains 52,898 LinkedIn users who have worked in 60 JVs and domestic firms. The spatial distribution of these users is consistent with the spatial distribution of automobile production: the correlation coefficient between the number of LinkedIn users in a province and the provincial automobile production in 2018 is 0.89. The two provinces with the largest auto production,

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

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

[14] Following the standard classification system, we classify models into eight segments: mini sedan, small sedan, compact sedan, medium sedan, large sedan, small-medium SUV, large SUV, MPV.

Guangzhou and Shanghai, also have the highest number of users in our data.

We identify 4,099 users who have moved at least once from one automobile company to another. For each job switch, we compile information on firm name and location before and after the switch, as well as worker characteristics such as current occupation and education level.[15] Our final sample covers 3,086 job switches after dropping observations with missing job location data. 617 of them moved from JVs to domestic firms. Such data allow us to examine the patterns of worker flows across firms that are related to knowledge spillover.

**Supplier network** Data on the auto-part supplier network is compiled from Marklines' Who Supplies Whom database.[16] Our final sample covers 1378 distinct part suppliers, 271 vehicle parts under 31 part categories, and 459 vehicle models.[17] Since data at the annual level is sparse, especially in early periods of our sample, we pool information from all years to construct the supplier network. Each auto-part company supplies on average 2.8 parts and to 11 vehicle models, and there is a small number of large suppliers that cover many parts and models. For an average model, we have supplier information on 39 vehicle parts. While the data is not complete enough to be regarded as a census of suppliers, it provides valuable information on the production network and captures the major suppliers for many models.

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

**Patent database** Data on patent transfers and licensing is collected by China's State Intellectual Property Office and cover the universe of patent transfers between any firms up till the most recent year. There are two types of transfers: patent licensing and patent assignment. The former is a

[15]Majority of workers who changed jobs switched once (81%) or twice (16%).

[16]Marklines collects the supplier information in a number of ways. Some information is directly sourced from supplier companies or downstream assembly firms. Some is obtained from vehicle tear-downs where supplier information is retrieved from the label or stamp on vehicle parts. Press releases and news articles are another important source.

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

temporary transfer of the property right from the patent owner to a licensee for a fee or royalties during a specified time period. The latter is a permanent transfer of the intellectual property right from the owner to the assignee for a lump sum upfront payment. This information allows us to examine the extent of market-based direct technology transfers between JVs and domestic firms.

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

### 2.3 Descriptive Patterns of Quality Upgrading

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

Figure 3 plots the dramatic improvement in the overall IQS score over time, summed across all nine quality dimensions, for JVs, affiliated SOEs, and non-affiliated domestic automakers, respectively. In 2009, JVs have significantly higher quality than the other two types: the number of defects per 100 vehicles was 143 for JV models, in contrast to 236 for models produced by affiliated domestic firms and 271 for those produced by non-affiliated domestic firms. By 2014, the overall IQS score of the domestic models has largely converged to that of the JVs': the number of defects per 100 vehicles is 94 for JV models, 123 for models by affiliated domestic firms, and 134 for those by non-affiliated firms. We observe similar convergence patterns in each of the quality dimension as shown in the second and third graphs of Figure 3. Our empirical strategy seeks to isolate the role of ownership affiliation under *quid pro quo* in driving the quality improvement of domestic models.[18]

Our second quality measure, APEAL scores, represents a more subjective evaluation of the driving experience. Panel B of Table 1 displays summary statistics of APEAL scores by year and ownership type. The change in APEAL scores over time is modest, in contrast to the significant improvement in

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

IQS scores. The comparison highlights that APEAL scores, measuring consumer satisfaction, may be affected by consumer perception and could evolve over time as consumers become more knowledgeable about quality. For example, owners of luxury models may have a higher expectation than owners of entry models, which could be reflected in their evaluations. Our empirical analysis addresses this issue by including a rich set of fixed effects (model by year, car segment by quality category, and quality category by year) to capture the difference in consumer perceptions across models and over time and only relying on *within-model* perceptions across different quality dimensions. We also perform robustness checks using IQS and APEAL scores separately and obtain very similar results.

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

# 3 Empirical Strategy

## 3.1 Empirical Framework

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

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

To address this issue, we exploit quality variation across different dimensions (nine IQS quality categories and ten APEAL performance categories) at the *model-pair* level. To ease the interpretation, we multiply the raw IQS scores by negative one, so that a larger IQS number (e.g., a less negative number) implies better quality (fewer defects), as does APEAL. We proceed in two steps. First, we construct the residualized (i.e., relative) quality strength for model $i$ in vehicle segment $s$ for quality category $k$ in year $t$ by partialing out fixed effects for model-year $it$ (e.g., Brilliance-BMW X3 series in 2014), segment-category $sk$ (e.g., fuel efficiency of compact sedans) and category-year $kt$ (e.g., driving experience in 2014):

$$\text{Score}_{iskt} = \lambda_{kt} + \lambda_{sk} + \lambda_{it} + \widetilde{\text{Score}}_{iskt} \quad (1)$$

The rich set of product level and temporal fixed effects in Equation (1) helps mitigate common unobservables that affect quality improvement. Category by year fixed effects control for category-specific time trends, such as an industry-wide improvement in the power train or the navigation system over time. Segment by category fixed effects capture factors that are specific to a vehicle segment and quality metric. For instance, vehicles in the luxury segment commonly adopt advanced technologies (such as lane change assist and blind spot assist that enhance vehicle safety) that other segments rarely use. Model by year fixed effects absorb time varying changes that affect the overall model quality.

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

$$\widetilde{\text{DMScore}}_{ijkt} = \alpha + \beta_0 \widetilde{\text{JVScore}}_{ijkt} + \widetilde{\text{JVScore}}_{ijkt} \times \text{Z}_{ij}\beta_1 + \epsilon_{ijkt} \quad (2)$$

where $\widetilde{\text{DMScore}}_{ijkt}$ and $\widetilde{\text{JVscore}}_{ijkt}$ are residualized scores for model pair $\{i, j\}$ in year $t$ and metric $k$. $\text{Z}_{ij}$ is a vector of pair attributes, such as whether the pair is produced by affiliated automakers (i.e., a SOE and its affiliated JVs), which is our primary focus. We also examine pairs that locate in the same city or 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 $\beta_0$ and $\beta_1$ relies on two sources of variation: the cross-sectional association in relative strength (or weakness) and contemporaneous co-movement in quality (net of overall time trend). Our identification strategy is best illustrated using a specific example. Figure 4 shows engine quality and fuel efficiency of four models, two by JVs (Brilliance-BMW and Dongfeng-Nissan) and two by the affiliated domestic automakers (Brilliance and Dongfeng). The JV model by Brilliance-BMW has a more reliable engine but is less fuel efficient than the model by Dongfeng-Nissan. The two domestic models that are produced by Brilliance and Dongfeng exhibit similar relative strength and weakness.

We take this as evidence of knowledge spillover. Our empirical analysis below examines whether such patterns hold true systematically.

Our empirical framework represents a significant departure from the existing literature on knowledge spillover from FDI to domestic firms, which mainly relies on variations at the industry level while controlling for standard panel fixed effects (Aitken and Harrison, 1999; Holmes, McGrattan, and Prescott, 2015; Jiang et al., 2018). The key identification concern is these fixed effects may be inadequate in controlling for other industry-time level shocks that affect both the entry of foreign firms and the performance of domestic firms, such as government policies targeting certain industries. By focusing on different dimensions of quality measures *within* a product-year, our analysis explores a much finer level of variation and allows us to control for *time-varying* unobservables at the firm and product level. At the same time, this rich set of controls soak out industry-wide quality improvement. Therefore, if spillover from JVs benefits both affiliated firms and non-affiliated firms by the same magnitude, the estimate of $\beta_1$ will not capture this – rightly so – as ownership affiliation is not required for this to happen.[19]

Finally, the two-step procedure illustrated in Equations (1) and (2) has significant advantages over the standard practice of one-step estimation with all the fixed effects. First, this allows us to control for the time-varying average quality for the domestic models and JV models separately. The standard one-step estimation can only control for the average quality for the followers. Second, as shown by Lee and Lemieux (2010), partialling out fixed effects first can increase the efficiency of key parameter estimates $\beta_1$ while maintaining consistency under very mild conditions.

### 3.2 Evidence of Relative Strength

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

To quantify the extent of similarity in quality strength among models produced by the same JV firm, we estimate Equations (1) and (2) using JV pairs. We randomly assign half of all JV models as leaders and the rest as followers. Then we take all models in a year to form an exhaustive list of pairs and compute the residualized scores for each JV model and regress follower scores on leader scores. This

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

exercise also serves as a proof of concept for our spillover analysis below. If the framework is capable of identifying relative strength among products within the same JV firm, we can use it to examine similarity in relative quality strength between JV models and domestics models.

As shown in Table 2, the coefficient estimate on the interaction term between LeaderScore and SameFirm, $\beta_1$, is positive and statistically significant.[20] It is also economically meaningful. When we control for firm fixed effects, as well as category-year and category-segment fixed effects, a reduction of 10 defects in a JV model is associated with a reduction of 1.4 defects in the same quality dimension among other models by the same firm. The coefficient is stable across different columns of Table 2, with different combinations of firm, firm-year, model, and model-year fixed effects. Such within-firm cross-model correlation corroborates with patterns documented in Figure 5. Firms indeed specialize in different quality dimensions, which enables our analysis below that examines spillover from JVs to domestic firms.

# 4 Results on Knowledge Spillover

## 4.1 Main Results

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

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

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

[20] As the follower and leaders are randomly assigned, the coefficient estimate of $\beta_0$ has no causal interpretation and is purely the correlation in quality between a random pair of models.

domestic firm is naturally weaker than that between two models from the same firm.

Column (2) adds interaction terms to flag pairs that belong to the same vehicle segment (SameSegment) and ownership group (SameGroup). Once we control for the interaction between SameGroup and SameSegment, the SameGroup coefficient becomes small and insignificant. This indicates that spillover occur primarily among products in the same segment (e.g., sedan or SUV). Therefore, for the remaining empirical analysis, we primarily focus on follower-leader pairs belonging to the same segment. In Columns (3) to (6), we gradually add more FEs to absorb firm-year, model and model-year variations. The results remain robust. Taking the most demanding specification in Column (6), our main specification, the coefficient estimate of the interaction between SameGroup and SameSegment is economically significant: 13.8% of the quality improvement observed in a JV model would be transmitted to the affiliated domestic models in the same segment. This is similar in magnitude to the estimated shared quality strength among models within the same JV firm but across different segments (Table 2).[21]

**Robustness checks** Our regressions so far are based on residualized quality measures after partialing out the model-year, score-segment, and score-year fixed effects, separately for leaders and followers. Table B.4 reports the results of running fixed effect regressions instead of taking residuals first, using the same fixed effect combinations as in Table 3. Mathematically, these regressions are not the same as the two-step procedure in Equations (1) and (2), but the estimates are similar and all of them suggest that knowledge spillovers occur in the same segment and same group.

Standard errors in Table 3 are two-way clustered by $i$'s firm and quality category as well as $j$'s firm and quality category. This allows for cross-sectional and temporal correlation of a given quality dimension (e.g., engine) across models in the same firm. Table B.5 reports the standard errors clustered in six different levels, including clustering by the leading firm and following firm, by the firm pair, or by firm-year. Our results are robust to all of these different levels of clustering.

Table B.6 analyzes the dynamic spillover effects based on leaders' past quality measures. As there is a proliferation of new models in our sample period, a large number of models are observed for only a short time span. For this exercise we use a balanced subsample of JV and domestic models that were sold every year between 2009 and 2014. Column (1) repeats the baseline regression. Knowledge spillover is stronger for this subsample than all affiliated model-pairs: the key coefficient $\beta_1$ is 0.258 vs 0.138 in Column (6) of Table 3. These are older and more popular models that have longer exposure to their leaders. Columns (2) to (4) lag a leader's quality score by one, two and three years. The coefficient of past leader score is remarkably persistent, even in the specification with a three-year lag. These results are consistent with a dynamic learning process: domestic firms observe production techniques of affiliated JVs models, gradually learn and incorporate them into their own production process.

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

### 4.2 Alternative Explanations

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

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

As discussed in Section 2.1, most major JVs in the Chinese auto industry were formed between the 1980s and the early 2000s, a period when domestic firms had limited technological capacity and few if any indigenous passenger vehicle brands (Figure B.1). Thus, it was difficult for the foreign firms to predict the strength/weakness of the potential Chinese partners decades later, let alone to base their partnership decisions on those predictions.

Nonetheless, we conduct two sets of analyses to formally gauge the importance of the selection effect in Table 4. Column (1) repeats our baseline specification. Column (2) restricts the sample to JVs that were formed prior to 2000, at a time that predates our sample period by nearly a decade and before the domestic passenger car industry took off. The estimates show that if anything, spillover is stronger from these older JVs, suggesting that our main finding is unlikely to be driven by endogenous ownership formation.

Second, to control for the initial (either negative or positive) correlation in quality measure between follower and leader pairs due to strategic considerations in JV formation, we control for *model by quality category* fixed effects in Column (3). This specification absorbs any time-invariant common strength (or weakness) among follower-leader pairs in each quality category. Thus, the identification relies only on temporal co-movement in quality measures, a source of variation that is likely to be exogenous to JV formation that occurred long before the domestic models were introduced. Our results of positive spillover from JVs to their affiliated domestic partners continue to hold under this demanding specification.

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

$$Log(\text{TopTwoChoices}_{ijt} + 1) = \alpha + X_{ijt}\beta + \lambda_t + \varepsilon_{ijt} \tag{3}$$

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

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

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

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

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

Among the 2,744 cases of patent assignment among automakers, none of them originated from a JV.

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

In sum, we have shown that domestic model share similar quality strength with affiliated JV models, and this pattern is not driven by endogenous JV formation, overlapping customer base or direct technology transfers.[22] The results support the interpretation of knowledge spillover via the ownership network. Next, we investigate potential underlying mechanisms of such knowledge spillover.

# 5 Mechanisms of Knowledge Spillover

The vehicle production process includes interrelated stages from product planning (e.g., market analysis), design and engineering (e.g., chassis, power train, exterior and interior), sourcing of parts and components, testing, and assembly. The whole process involves complex interactions of technologies, equipment, and workers. Knowledge spillover could occur during all stages of the production process and through many different channels, including deliberate communication among the partners, flow of know-how through shared parts suppliers, knowledge exchange embodied in workers changing jobs, etc. In this section, we examine two potential mechanisms, namely worker flows and supplier network. We focus on pairs of domestic and JV models in the same vehicle segment, for which we have observed the strongest spillover effect (Table 3). The main takeaways are robust when we expand the sample to include all pairs.[23]

## 5.1 Worker Flows

Using job switches that are compiled from user profiles on LinkedIn (China), we first document that workers are considerably more likely to move from JVs to affiliated SOEs or to another firm in the same city. Among all workers who switched jobs from a JV to a domestic firm, 27.2% moved to the JV's affiliated domestic firm, and 36.1% moved to other firms in the same city. These fraction would have been 9.3% and 7.7% if worker movement were random.[24]

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

[23]The results are available upon request.

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

We then examine the extent to which worker flow mediates knowledge spillover through ownership affiliation. We measure the intensity of worker flow using the number of job switchers between each pair of JV and domestic firms and standardize it across all observations. Then we interact worker flow with the same-group dummy. Table 7 summarizes the results. Column (1) shows that spillover is on average 14.3% between affiliated pairs. Column (2) shows that spillover is 6.3% when worker flow is at the national average, and increases by 3% for each standard-deviation increase in the volume of worker flow. The estimates suggest that worker flow explains 58% of knowledge spillover from JVs to affiliated firms.[25]

Some underlying factors, such as closer connections between firms, could result in both a larger worker flow and more knowledge spillover. Column (3) additionally controls for the reverse worker flow from the domestic firm to the JV, which is a proxy for business connections between the two firms. We find similar effects for JV-to-domestic worker flows, and no appreciable effect for domestic-to-JV flows. The asymmetric results are consistent with anecdotal evidence that domestic firms benefit from recruiting technicians with working experience at JVs, especially in key production areas with technology bottlenecks (Liu, 2019). Column (4) examines whether the effect is larger for the flow of skilled workers. To do that, we limit the sample to observations with positive JV-to-domestic flows and compute the share of technicians, classified based on job titles.[26] Consistent with the previous literature (e.g., Poole (2013b)), we find that knowledge spillover is positively correlated with the movement of technicians, though the coefficient on the additional interaction term is not precisely estimated.

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

moving from A to B would be 6% if the flow is random.

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

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

### 5.2 Supplier Network

Supply network could serve as another important conduit for knowledge spillover. This is especially true for the automobile industry where quality of parts and components is a key determinant of a vehicle's performance. The presence and growth of JVs have been argued to have helped and incentivized domestic part suppliers to improve their product quality, which also benefited domestic automakers.[27] JVs' sourcing decisions may also provide valuable information to domestic partners and help the latter identify reliable and high-quality suppliers. Here we examine the importance of this shared supplier spillover.

Our data affirm that ownership linkages have a sizable impact on supplier overlap. Affiliated model pairs share on average 12 common suppliers, compared to an average of 5.4 common suppliers between non-affiliated pairs.[28] We examine to what extent the shared quality strength between affiliated pairs could be driven by common part suppliers. For each model pair, we compute the Szymkiewicz-Simpson overlap ratio, which equals to the number of common suppliers divided by the smaller number of suppliers among the two firms. Then we standardize the overlap ratio across all observations and interact the standardized overlap ratio with the same-group dummy.[29] Table 8 reports results. A larger supplier overlap is indeed associated with stronger knowledge spillover. Estimates from Columns (1) and (2) imply that supplier overlap explains 32% of the knowledge spillover via ownership affiliation.[30]

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

# 6 Policy Implications

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

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

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

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

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

selection, it does leave open the question of whether we can extrapolate our findings to shed light on what would happen in the absence of *quid pro quo*.

In addition, a skeptical view of the findings above is that spillover to non-affiliated firms could only happen with some form of *quid pro quo* in place, and that affiliated domestic partners are crucial 'conduits' for knowledge to flow from foreign firms to domestic firms. Once a firm becomes wholly foreign-owned, it can manage to silo its know-how, resulting in fundamentally different spillover patterns.

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

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

**Are affiliated domestic firms necessary for knowledge spillover?** Next, we ask whether affiliated domestic firms are in fact necessary conducts for knowledge to flow to unaffiliated firms. While the *quid pro quo* policy is nationwide, we do observe cities that host non-affiliated domestic firms together with JVs, however, without the presence of affiliated domestic firms (see Figure B.4). This constitutes a close analogue of the counterfactual, since these cities do not have the affiliated domestic firms serving as the 'conduit' of knowledge spillover.

Therefore, in the second analysis, we limit the sample to a subset of cities that host a JV plant and non-affiliated domestic plants, but none of the affiliated domestic plants.[31] If the presence of an

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

affiliated domestic firm is crucial in mediating knowledge spillover to other non-affiliated domestic firms, we would expect the latter to benefit less from a JV in the absence of the former. Results are reported in Table 10. The two key regressors are whether the model pair is located in cities with or without any affiliated domestic plant.[32] If anything, the spillover from JVs to non-affiliated domestic firms in the same city is larger when there are no affiliated domestic firm, with a p-value of 0.016 for the equality of these two coefficients. This suggests that the presence of affiliated firms is not a necessary conduit for knowledge spillover, which could happen via channels other than ownership affiliation.

**Evidence from the auto parts industry** While the downstream auto assembly industry is subject to *quid pro quo*, the upstream parts and components industry features a dynamic environment with both JVs and wholly foreign-owned firms, and considerable variation in ownership composition across cities (as shown in Figure B.5).[33] Our third analysis further leverages the variation in ownership type in the upstream industry to examine whether wholly foreign-owned FDIs benefit domestic firms significantly less in terms of knowledge spillover compared to JVs.

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

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

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

Table 11 shows the regression results. The results are qualitative robust across columns with different

[32] The sample consists of model pairs between non-affiliated domestic firms and JVs. The omitted group is non-affiliated domestic-JV pairs in different cities.

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

combinations of fixed effects.[34] While domestic firms appear to benefit more from foreign firms located in the same city (Columns (1) and (3)), whether the latter is a wholly foreign-owned entity or a joint venture does not appear to matter (Columns (2) and (4)). We do not find evidence that knowledge spillover from wholly foreign-owned FDIs is significantly less than that from joint ventures.

In general, the existing literature has documented mixed evidence on whether domestic firms benefit more from JVs compared to wholly foreign-owned firms. For example, Blomström and Sjöholm (1999) show that the degree of foreign ownership at the industry level does not affect the degree of spillover to domestic firms. On the other hand, using firm-level data from Lithuania and Romania, respectively, Javorcik (2004) and Javorcik and Spatareanu (2008) document spillover to upstream suppliers (vertical spillover) from joint ventures but not from wholly foreign-owned investment. Conceptually speaking, whether the spillover is stronger from JVs depends on the absorptive capacity of domestic firms, technology gaps between the two and the nature of competition. Our finding from the upstream parts and components sector is probably more relevant for the auto industry, given the similarity in technology progress and the absorptive capacity of domestic firms.

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

We experiment with two different assumptions on the dynamics of knowledge spillover. The first scenario assumes that knowledge spillover and learning are proportional to the difference between current JV model quality and domestic model's quality in 2009.[35] The second scenario assumes that learning occurs cumulatively each year. The benefit affiliated domestic firms 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.[36] 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

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

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

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

to bound our predictions on the effects of *quid pro quo*.

Figure 6 shows results based on our baseline estimate in Table 3. We use total IQS score as the quality measure of interest. The solid lines plot observed annual average IQS scores for JV, affiliated domestic models, and non-affiliated domestic models. The dashed line plots the predicted quality of affiliated domestic model in the absence of *quid pro quo*. In the first scenario, lifting *quid pro quo* in 2010 would reduce average domestic quality in 2014 by 9% (around 12 more defects per model) for affiliated models, and 5.7% for all domestic models. Without *quid pro quo*, the affiliated domestic firms, all of which are SOEs, would have been outperformed by their non-affiliated counterparts by 2014. With cumulative learning, the effect increases to a 23% reduction (around 33 more defects per model) for affiliated models and 16.5% for all domestic models. Note that in both exercises, any industry-wide knowledge spillover due to the presence of foreign firms, absorbed by quality category by year fixed effects and quality category by segment fixed effects, is kept the same. Thus the key focus is on the role of *quid pro quo*'s stipulated ownership requirement.

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

## 7 Conclusion

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

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

## References


Aghion, Philippe, Antoine Dechezlepretre, David Hemous, Ralf Martin, and John Van Reenen. 2016. "Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry." Journal of Political Economy 124 (1):1–51.

Aitken, Brian J and Ann E Harrison. 1999. "Do domestic firms benefit from direct foreign investment? Evidence from Venezuela." American economic review 89 (3):605–618.

Atkin, David, Amit K Khandelwal, and Adam Osman. 2017. "Exporting and firm performance: Evidence from a randomized experiment." The Quarterly Journal of Economics 132 (2):551–615.

Balsvik, Ragnhild. 2011. "Is labor mobility a channel for spillovers from multinationals? Evidence from Norwegian manufacturing." The review of economics and statistics 93 (1):285–297.

Barwick, Panle Jia, Myrto Kalouptsidi, and Nahim Bin Zahur. 2019. "China's Industrial Policy: an Empirical Evaluation." Tech. rep., National Bureau of Economic Research.

Bastos, Paulo, Joana Silva, and Eric Verhoogen. 2018. "Export destinations and input prices." American Economic Review 108 (2):353–92.

Bilir, L Kamran and Eduardo Morales. 2016. "Innovation in the global firm." Tech. rep., National Bureau of Economic Research.

Blalock, Garrick and Paul J Gertler. 2008a. "Welfare gains from foreign direct investment through technology transfer to local suppliers." Journal of international Economics 74 (2):402–421.

Blalock, Garrick and Paul J. Gertler. 2008b. "Welfare gains from Foreign Direct Investment through technology transfer to local suppliers." Journal of International Economics 74 (2):402 – 421.

Blomström, Magnus and Fredrik Sjöholm. 1999. "Technology transfer and spillovers: Does local participation with multinationals matter?" European Economic Review 43 (4):915 – 923.

Boschma, Ron, Rikard Eriksson, and Urban Lindgren. 2009. "How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity." Journal of Economic Geography 9 (2):169–190.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO accession and performance of Chinese manufacturing firms." American Economic Review 107 (9):2784–2820.

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. 2012. "Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing." Journal of development economics 97 (2):339–351.

Buera, Francisco J and Ezra Oberfield. 2016. "The global diffusion of ideas." Tech. rep., National Bureau of Economic Research.

Castillo, Victoria, Lucas Figal Garone, Alessandro Maffioli, Sofia Rojo, and Rodolfo Stucchi. 2020. "Knowledge Spillovers through Labour Mobility: An Employer–Employee Analysis." The Journal of Development Studies 56 (3):469–488.

Chen, Yuan and C-Y Cynthia Lin Lawell. 2019. "Supply and Demand in the Chinese Automobile Market: A Random Coefficients Mixed Oligopolistic Differentiated Products Model." Working Paper.

Chen, Yuan, C-Y Cynthia Lin Lawell, and Yunshi Wang. 2020. "The Chinese automobile industry and government policy." Research in Transportation Economics :100849.

Chen, Yuyu, Mitsuru Igami, Masayuki Sawada, and Mo Xiao. 2019. "Privatization and Productivity in China." Working Paper.

Eslava, Marcela, Ana Cecília Fieler, and Daniel Yi Xu. 2015. "(Indirect) Input Linkages." American Economic Review 105 (5):662–66.

Fieler, Ana Cecília, Marcela Eslava, and Daniel Yi Xu. 2018. "Trade, quality upgrading, and input linkages: Theory and evidence from colombia." American Economic Review 108 (1):109–46.

Fosfuri, Andrea, Massimo Motta, and Thomas Rønde. 2001. "Foreign direct investment and spillovers through workers' mobility." Journal of international economics 53 (1):205–222.

Gallagher, Kelly Sims. 2003. "Foreign technology in China's automobile industry: implications for energy, economic development, and environment." China Environment Series) :1–18.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported intermediate inputs and domestic product growth: Evidence from India." The Quarterly journal of economics 125 (4):1727–1767.

Görg, Holger and Eric Strobl. 2005. "Spillovers from foreign firms through worker mobility: An empirical investigation." Scandinavian Journal of Economics 107 (4):693–709.

Gorodnichenko, Yuriy, Jan Svejnar, and Katherine Terrell. 2014. "When does FDI have positive spillovers? Evidence from 17 transition market economies." Journal of Comparative Economics 42 (4):954 – 969.

Haddad, Mona and Ann Harrison. 1993. "Are there positive spillovers from direct foreign investment?: Evidence from panel data for Morocco." Journal of Development Economics 42 (1):51 – 74.

Haskel, Jonathan E., Sonia C. Pereira, and Matthew J. Slaughter. 2007. "Does Inward Foreign Direct Investment Boost the Productivity of Domestic Firms?" The Review of Economics and Statistics 89 (3):482–496.

Havranek, Tomas and Zuzana Irsova. 2011. "Estimating vertical spillovers from FDI: Why results vary and what the true effect is." Journal of International Economics 85 (2):234 – 244. URL http://www.sciencedirect.com/science/article/pii/S002219961100081X.

Holmes, Thomas J, Ellen R McGrattan, and Edward C Prescott. 2015. "Quid pro quo: technology capital transfers for market access in China." The Review of Economic Studies 82 (3):1154–1193.

Hsieh, Chang-Tai and Zheng Michael Song. 2015. "Grasp the large, let go of the small: the transformation of the state sector in China." Tech. rep., National Bureau of Economic Research.

Igami, Mitsuru and Kosuke Uetake. 2019. "Mergers, Innovation, and Entry-Exit Dynamics: Consolidation of the Hard Disk Drive Industry, 1996?2016." The Review of Economic Studies .

Javorcik, Beata. 2004. "Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages." American economic review 94 (3):605–627.

Javorcik, Beata Smarzynska and Mariana Spatareanu. 2008. "To share or not to share: Does local participation matter for spillovers from foreign direct investment?" Journal of Development Economics 85 (1):194 – 217.

Jiang, Kun, Wolfgang Keller, Larry D. Qiu, and William Ridley. 2018. "International Joint Ventures and Internal versus External Technology Transfer: Evidence from Chin." CEPR Discussion Paper 12809.

Kalouptsidi, Myrto. 2017. "Detection and impact of industrial subsidies: The case of Chinese shipbuilding." The Review of Economic Studies 85 (2):1111–1158.

Karabay, Bilgehan. 2010. "Foreign direct investment and host country policies: A rationale for using ownership restrictions." Journal of Development Economics (93):218–225.

Kee, Hiau Looi. 2015. "Local intermediate inputs and the shared supplier spillovers of foreign direct investment." Journal of Development Economics 112 (C):56–71.

Kee, Hiau Looi and Heiwai Tang. 2016. "Domestic Value Added in Exports: Theory and Firm Evidence from China." American Economic Review 106 (6):1402–1436.

Keller, Wolfgang. 2004. "International Technology Diffusion." Journal of Economic Literature 42 (3):752–782.

———. 2010. "Chapter 19 - International Trade, Foreign Direct Investment, and Technology Spillovers." In Handbook of the Economics of Innovation, Volume 2, Handbook of the Economics of Innovation, vol. 2, edited by Bronwyn H. Hall and Nathan Rosenberg. North-Holland, 793 – 829.

Keller, Wolfgang and Stephen R Yeaple. 2009. "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States." The Review of Economics and Statistics 91 (4):821–831. URL https://doi.org/10.1162/rest.91.4.821.

Khandelwal, Amit. 2010. "The long and short (of) quality ladders." The Review of Economic Studies 77 (4):1450–1476.

Knittel, Christopher R. 2011. "Automobiles on Steroids: Product Attribute Trade-Offs and Technological Progress in the Automobile Sector." American Economic Review 101 (7):3368–99.

Kosova, Renata. 2010. "Do Foreign Firms Crowd Out Domestic Firms? Evidence from the Czech Republic." The Review of Economics and Statistics 92 (4):861–881. URL https://doi.org/10.1162/REST_a_00035.

Lee, David S and Thomas Lemieux. 2010. "Regression discontinuity designs in economics." Journal of economic literature 48 (2):281–355.

Liu, Jianli. 2019. "History of China's Foreign Capital Utilization Since 1949: Stage Characteristics, Positive Effect and Main Experience." Management World (11).

Lu, Yi, Zhigang Tao, and Lianming Zhu. 2017. "Identifying FDI spillovers." Journal of International Economics 107:75 – 90.

Maliranta, Mika, Pierre Mohnen, and Petri Rouvinen. 2009. "Is inter-firm labor mobility a channel of knowledge spillovers? Evidence from a linked employer–employee panel." Industrial and Corporate Change 18 (6):1161–1191.

Møen, Jarle. 2005. "Is mobility of technical personnel a source of R&D spillovers?" Journal of labor economics 23 (1):81–114.

Poole, Jennifer P. 2013a. "Knowledge transfers from multinational to domestic firms: Evidence from worker mobility." Review of Economics and Statistics 95 (2):393–406.

Poole, Jennifer P. 2013b. "Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility." The Review of Economics and Statistics 95 (2):393–406.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti. 2011. "Growing like china." American economic review 101 (1):196–233.

Stoyanov, Andrey and Nikolay Zubanov. 2012a. "Productivity spillovers across firms through worker mobility." American Economic Journal: Applied Economics 4 (2):168–98.

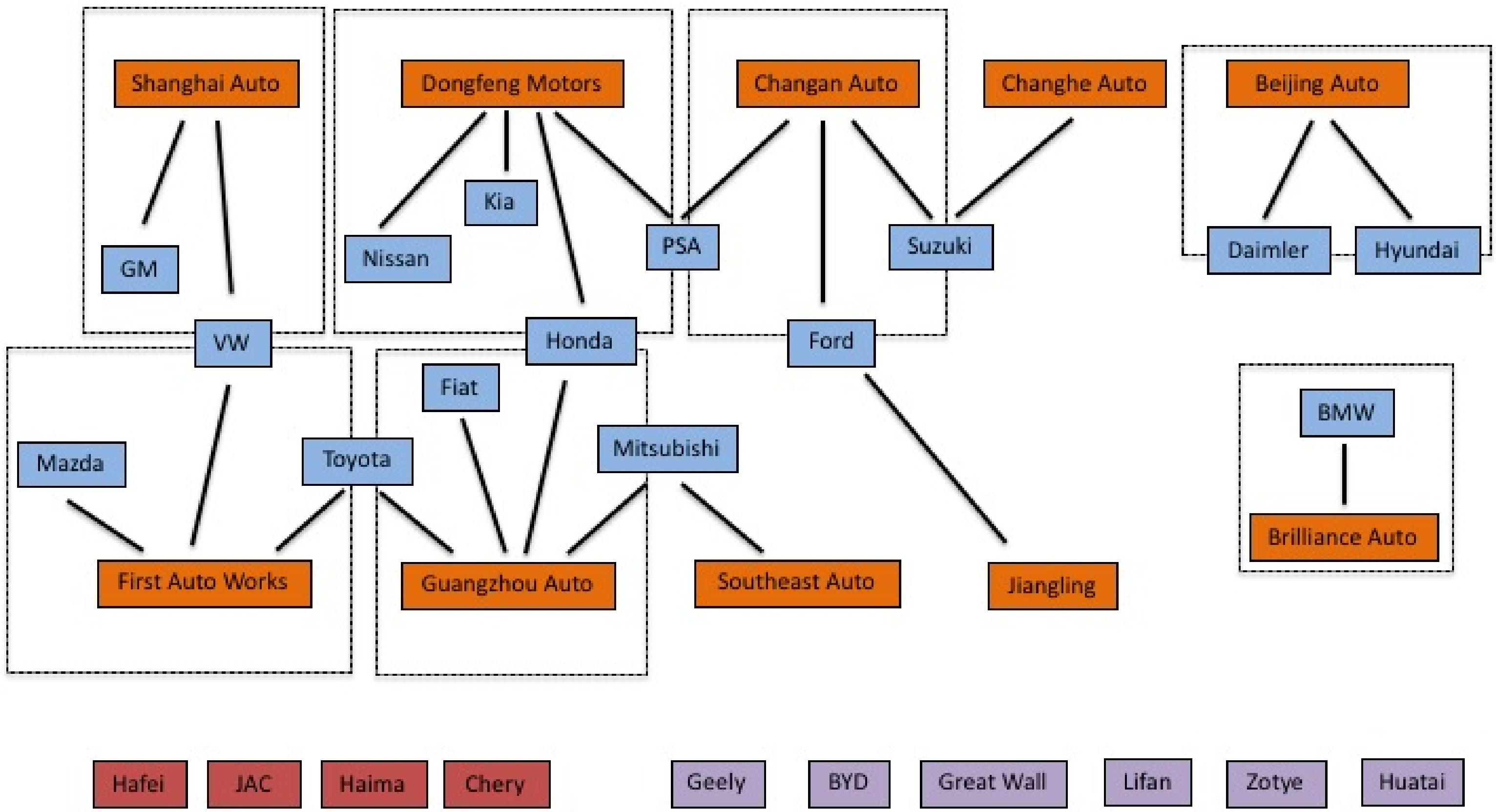
———. 2012b. "Productivity Spillovers across Firms through Worker Mobility." American Economic Journal: Applied Economics 4 (2):168–98.

UNCTAD. 2018. World investment report 2018: Investment and new industrial policies. UN.

World Bank, Bank. 2018. "Global investment competitiveness report 2017/2018: Foreign investor perspectives and policy implications."

Yu, Miaojie. 2015. "Processing trade, tariff reductions and firm productivity: evidence from Chinese firms." The Economic Journal 125 (585):943–988.

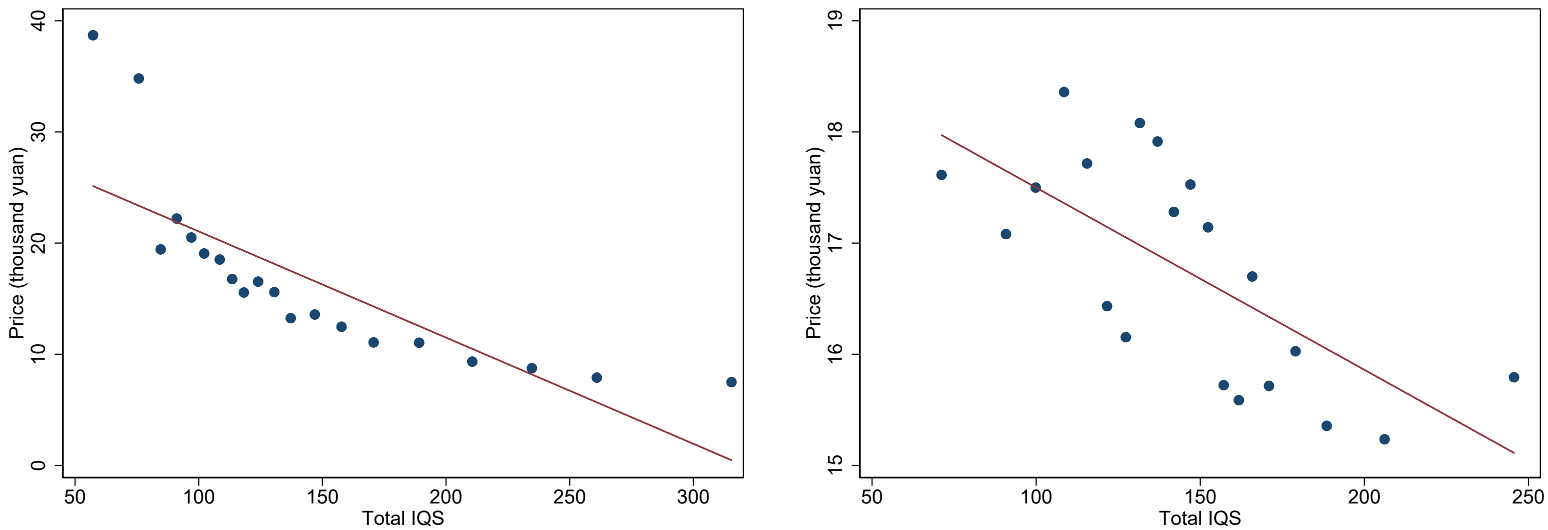
Figure 1: Joint Venture Network of the Chinese Auto Industry



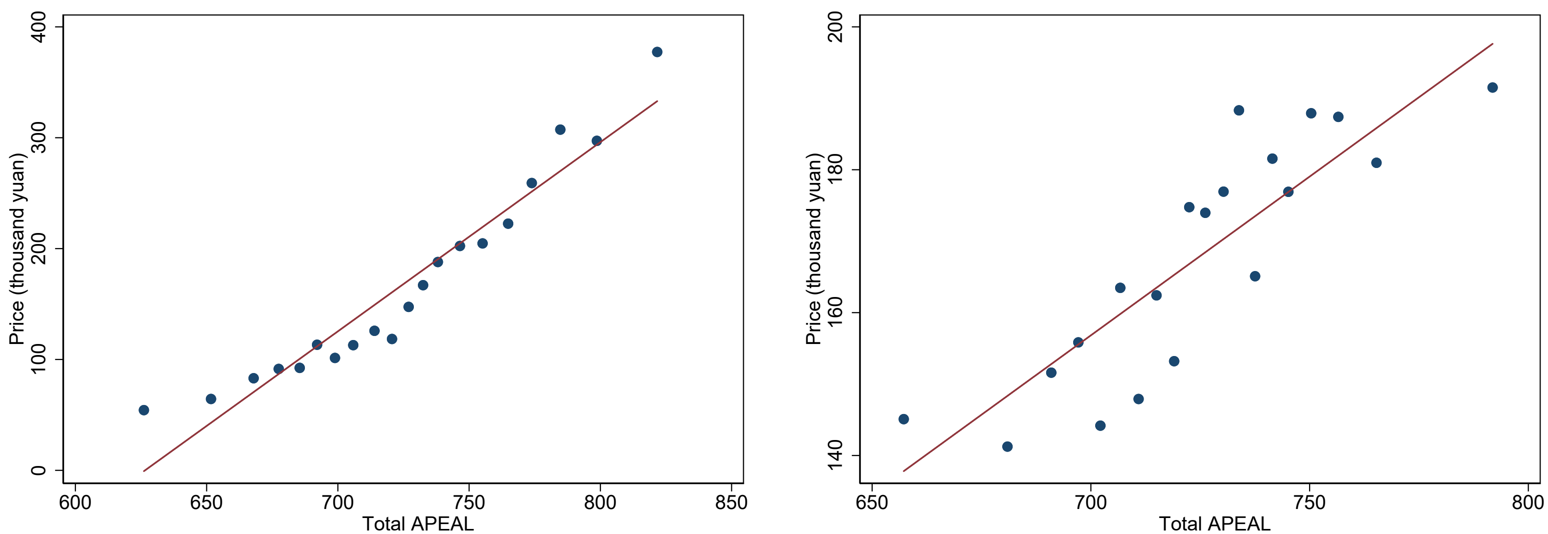

*Notes*: This figure is adapted from Figure 1 of Chen, Lawell, and Wang (2020). It describes the joint venture network of the Chinese auto market as of 2014. Orange boxes represent affiliated SOEs; blue boxes represent foreign partners in JVs; purple boxes represent private domestic firms; red boxes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

Figure 2: Correlation between Vehicle Price and IQS Scores

Panel A. Vehicle Price vs. IQS

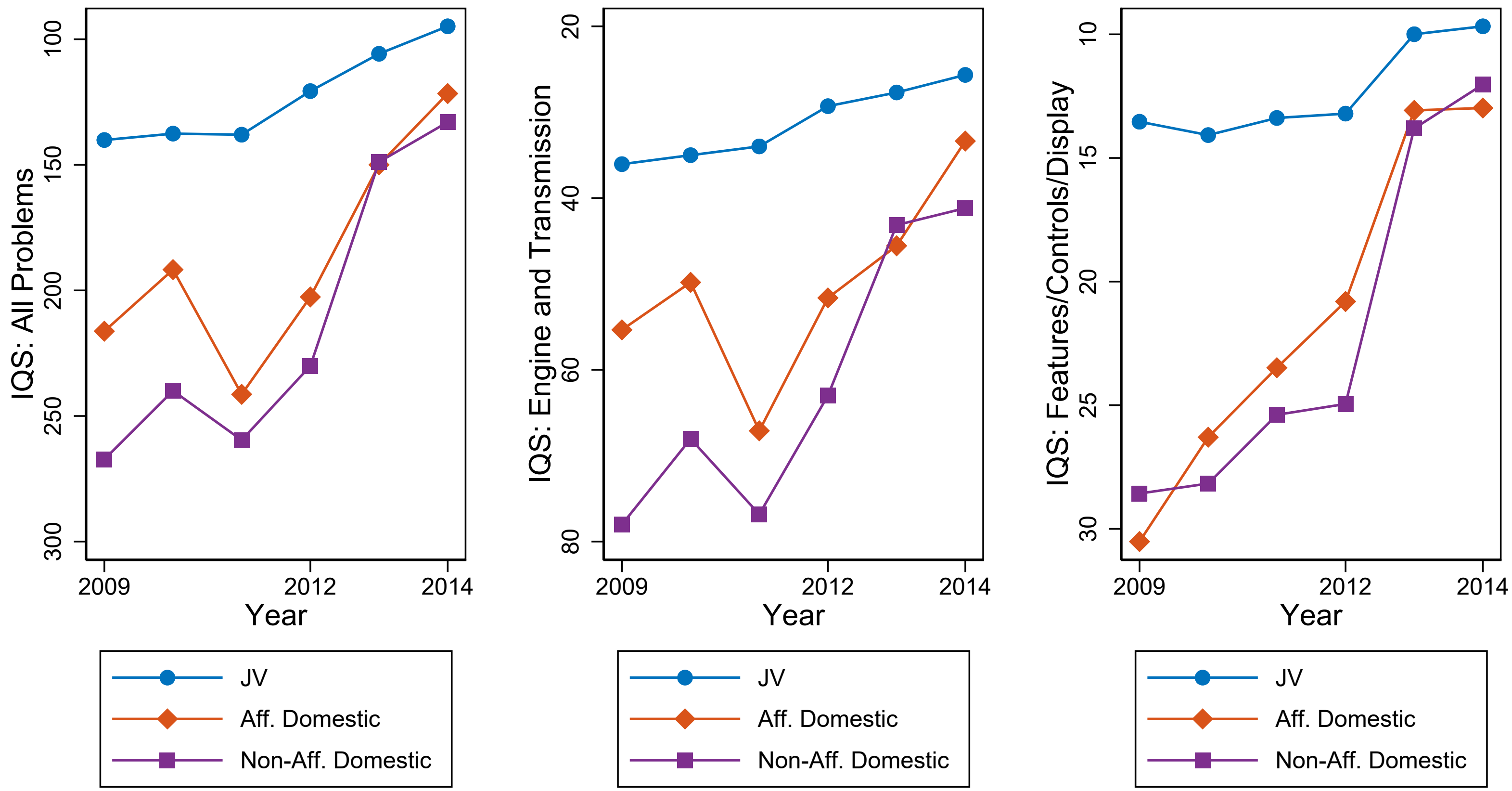



Panel B. Vehicle Price vs. APEAL



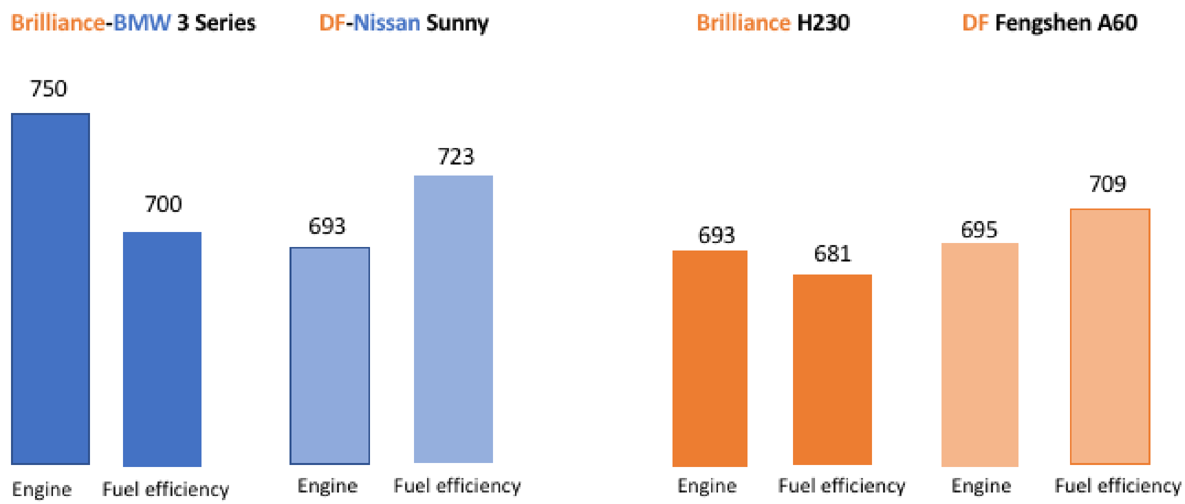

*Notes*: The figures are binned scatter plots between price and IQS (Panel A) and between price and APEAL (Panel B) The left figures control for vehicle size and horsepower/weight and the right figures further control for year fixed effects, segment fixed effects, and ownership type fixed effects. A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

Figure 3: Descriptive Patterns of Quality Upgrading



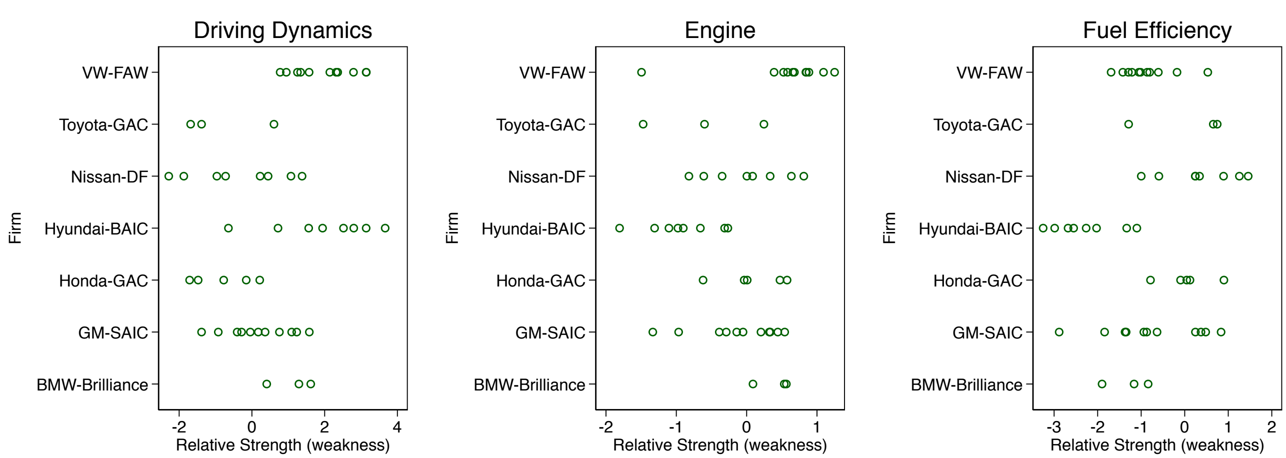

*Notes*: The vertical axis reports IQS scores, which is the number of problems experienced per 100 vehicles during the first 90 days of ownership across nine performance dimensions. Smaller numbers indicate higher quality. The aggregate score (left figure) is the sum of scores over the nine categories. The middle and right figures show the time dynamics of two categories, namely engine and transmission and features/control/display.

Figure 4: Leader-Follower Pattern of Relative Quality Strength



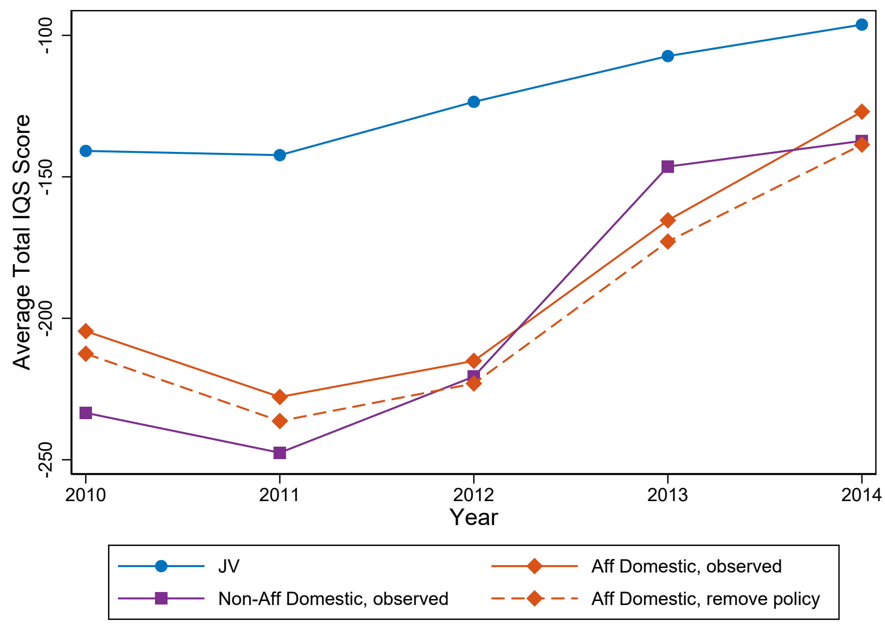

*Notes*: The bars show the quality scores for engine and fuel efficiency dimensions. The two models on the left are produced by JVs and those on the right are indigenous brands by affiliated domestic automakers.

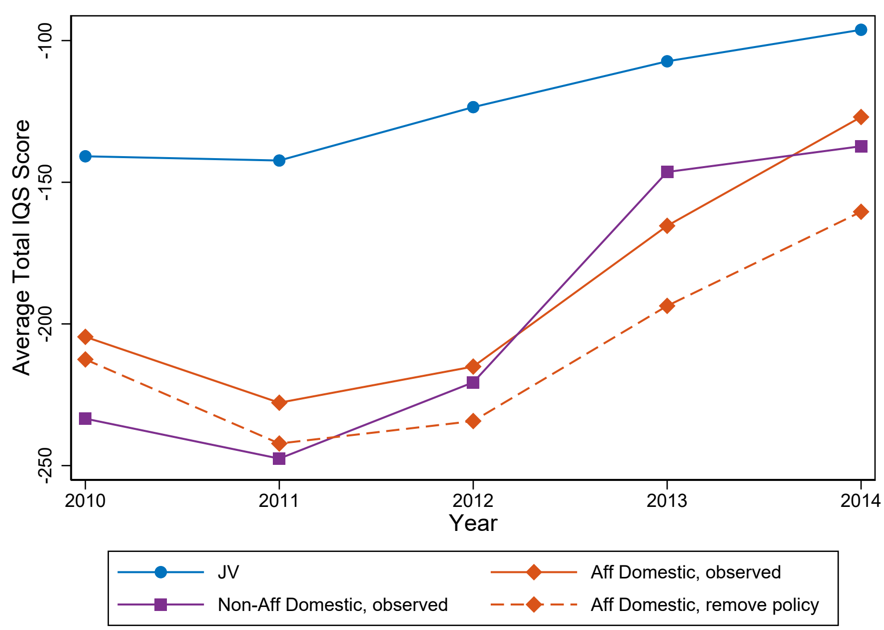
Figure 5: Differential Relative Quality Strength Among Leaders




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

Figure 6: Effects of Lifting *Quid Pro Quo* in 2010




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

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

Table 2: Relative Quality Strength among JVs

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

*Notes*: We randomly assign each JV model to be either a follower or a leader (with 50% chance each), and match each leader and follower in each each into pairs. The dependent variable is the quality score of a follower model. The unit of observation is a pair-year-quality category. Both leader and follower scores are residualized scores after taking out a set of fixed effects specified under each column. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 3: Knowledge Spillover from JVs to Domestic Firms

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

*Notes*: The dependent variable is the quality score of a domestic model. We consider all pairs of models produced by JVs and domestic firms. The unit of observation is a pair-year-quality category. Both leader (JV) and follower (domestic) scores are residualized scores after taking out various fixed effects. SameGroup is an indicator variable that equals to 1 if the two models belong to a pair of affiliated firms. SameSeg is an indicator variable that equals to 1 if the two models belong to the same vehicle segment. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 4: Results on Endogenous JV Formation

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

*Notes*: The dependent variable is the quality score of a domestic model. We consider pairs of models produced by JVs and domestic firms. Column (1) replicates our main result (Column (6) of Table 3). Column (2) restrict to models produced by JVs that are formed prior to 2000. In Column (3), we construct residualized leader (JV) and follower (domestic) scores by partialing out category-year and category-model fixed effects. This specification only exploits temporal variation in leader's quality. SameGroup and SameSeg are defined as in Table 3 Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 5: Alternative Explanation: Overlapping Customer Base

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

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

Table 6: Knowledge Spillover by IQS and APEAL Studies

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

*Notes*: Column (1) replicates Column (2) of Table 3. Columns (2) and (3) split IQS and APEAL scores into different regression samples. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 7: Mechanism of Knowledge Spillover: Worker Flow

| JVScore interacted with | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| × SameGroup | 0.143*** | 0.063*** | 0.046*** | 0.055*** |
| | (0.020) | (0.019) | (0.020) | (0.025) |
| × SameGroup × JVDomFlow | | 0.030*** | 0.026** | 0.037*** |
| | | (0.008) | (0.010) | (0.011) |
| × SameGroup × DomJVFlow | | | 0.012 | |
| | | | (0.011) | |
| × SameGroup × JVDomFlow × HighTechShare | | | | 0.044 |
| | | | | (0.041) |
| Observations | 115,159 | 115,159 | 115,159 | 51,585 |
| ***Partialing out:*** | | | | |
| Model-year FE | ✓ | ✓ | ✓ | ✓ |
| Category-Year FE | ✓ | ✓ | ✓ | ✓ |
| Category-Segment FE | ✓ | ✓ | ✓ | ✓ |

*Notes*: The sample consists of domestic-JV pairs in the same vehicle segment. The unit of observation is a pair-year-quality category. Both JV and domestic scores are residualized scores after taking out category-year, model-year and category-segment fixed effects. SameGroup is defined as in Table 3. JVDomFlow measures the number of workers who moved from the JV to the domestic firm. Vice versa for DomJVFlow. We identify six "HighTech" occupations that are directly related to the IQS quality measures. Those are feature designers, mechanical engineers, software engineers, procurement manager, quality control, and R&D. HighTechShare is the fraction of worker flows that is in one of the six occupations. All pairs with 0 worker flow (and hence undefined HighTechShare) are dropped in column (4). Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 8: Mechanism of Knowledge Spillover: Supplier Network

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

*Notes*: The sample consists of domestic-JV pairs in the same vehicle segment. The unit of observation is a pair-year-quality category. Both JV and domestic scores are residualized scores after taking out category-year, model-year and category-segment fixed effects. SameGroup is defined as in Table 3. SupplierOverlapRatio is defined as the number of common suppliers divided by the number of distinct suppliers reported by the pair (the smaller number of the two). Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

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

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

*Notes*: The dependent variable is the quality score of a domestic model. The sample consists of pairs of domestic-JV models in the same vehicle segment. The unit of observation is a pair-year-quality category. Both leader (JV) and follower (domestic) scores are residualized scores after taking out category-year, model-year and category-segment fixed effects. Interaction terms are dummy variables indicating whether the two models belong to the same affiliated group of firms or locate in the same city. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

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

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

*Notes*: The dependent variable is the quality score of a domestic model. The sample consists of pairs of models produced by JVs and non-affiliated domestic firms. The unit of observation is a pair-year-quality category. Both leader (JV) and follower (domestic) scores are residualized scores after taking out model-year, category-year and category-segment fixed effects. SameCity is an indicator variable that equals to 1 if the two models are produced in the same city. CityWithAffiliatedFirm and CityWithoutAffiliatedFirm are dummy variables indicating whether the city hosts an auto assembly plant by an affiliated domestic firm. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

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

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

*Notes*: The dependent variable is the quality of a domestic part suppliers. We consider all pairs of domestic and foreign/JV firms. The unit of observation is a pair-part category-year. Both the leader and follower scores are residualized after taking out fixed effects that are indicated at the bottom of the table. SameCity is an indicator variable that equals to 1 if the two firms are located in the same city. WhollyForeignOwned is an indicator variable that equals to 1 if the leader is a wholly foreign-owned firm and 0 if it is a joint venture. Standard errors are clustered at the follower-category and leader-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

# Appendices. For Online Publication Only

## A A Simple Model of Knowledge Spillover

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

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

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

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

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

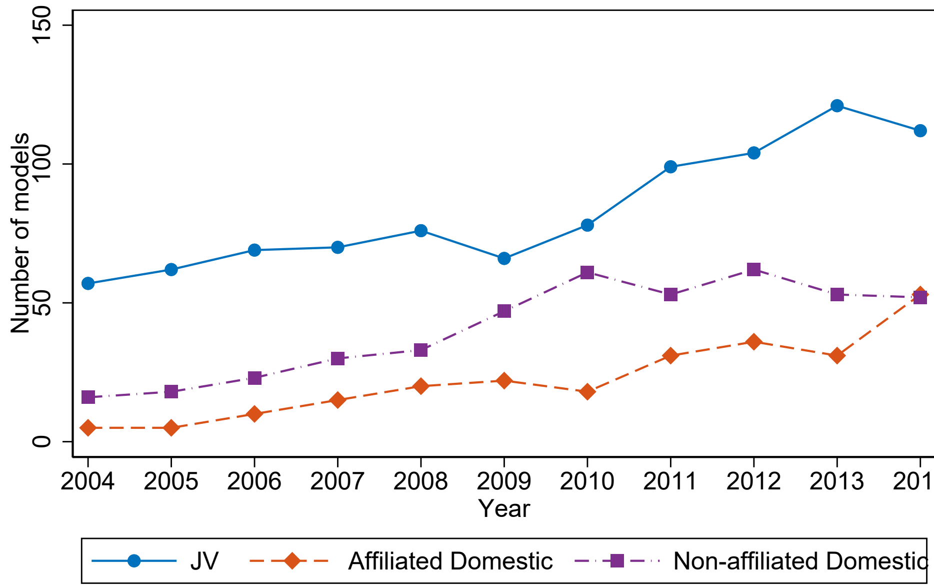
$$\xi_t^k = \rho\mu_t^k + (1-\rho)\varepsilon_t^k \tag{A.3}$$

This expression maps to our pairwise empirical framework. Intuitively, knowledge spillover translates into similar quality strength between the leader and the follower. $\varepsilon_t^k$, or the intrinsic quality strength of follower in the absence of spillover, shows up as a noise in the estimation. The identification assumption is that the follower's intrinsic quality strength $\varepsilon_t^k$ is independent from the leader's quality strength $\mu_t^k$. 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 $\rho$ using our reduced-form estimates, and use Equation (A.1) to back out knowledge spillover between each leader-follower pair in each year. For domestic models with multiple leaders, with calculate average spillover from the set of leaders. The reduction in quality of a follower when *quid pro quo* was lifted in 2009 s the sum of spillover between 2009 and year $t$.

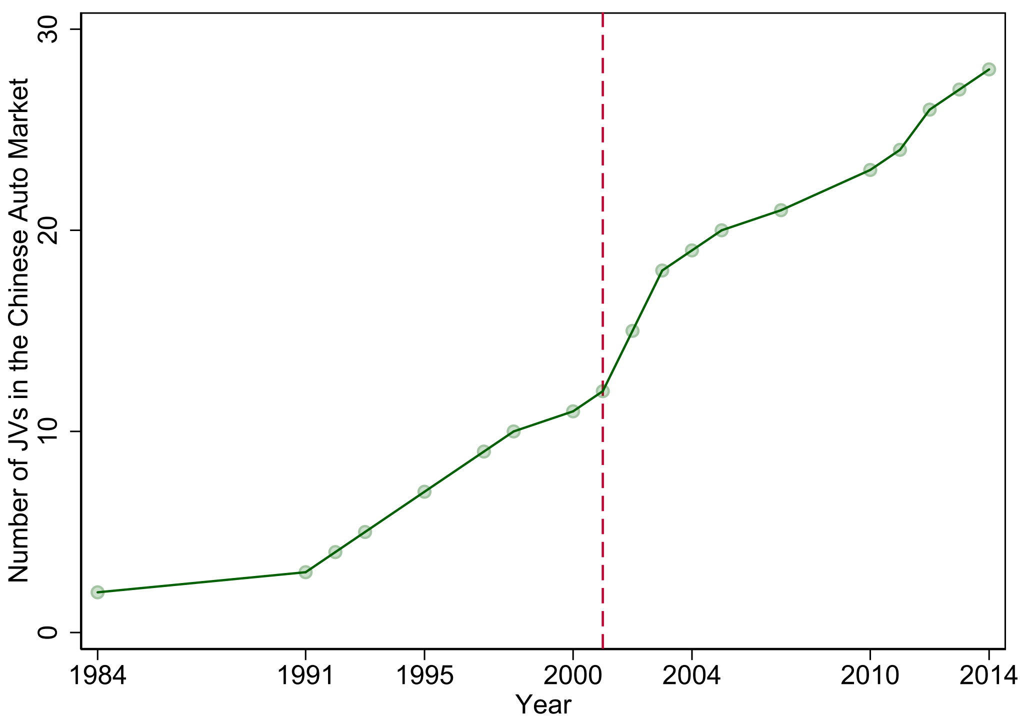
# B Figures and Tables

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




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

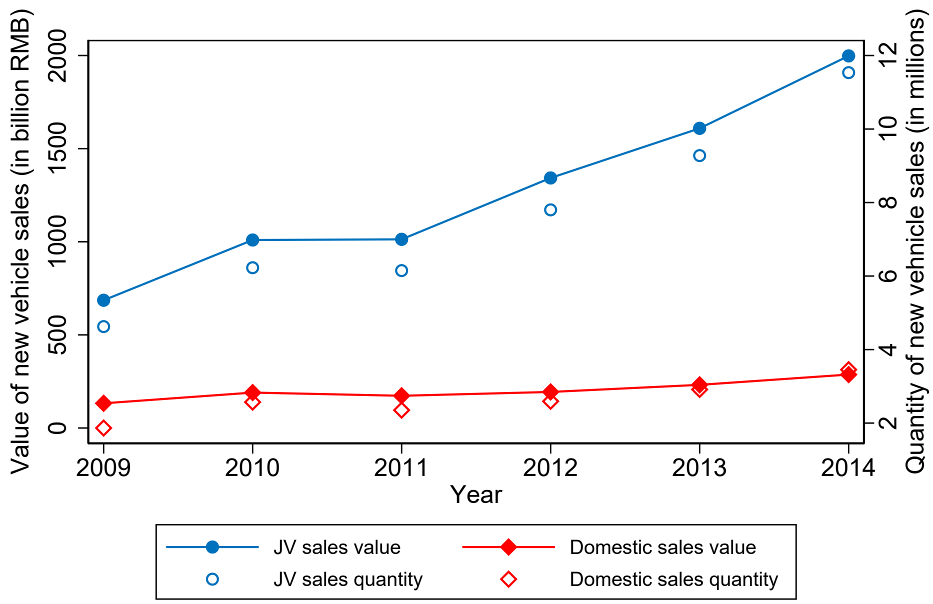
Figure B.2: Entry of International Joint Ventures



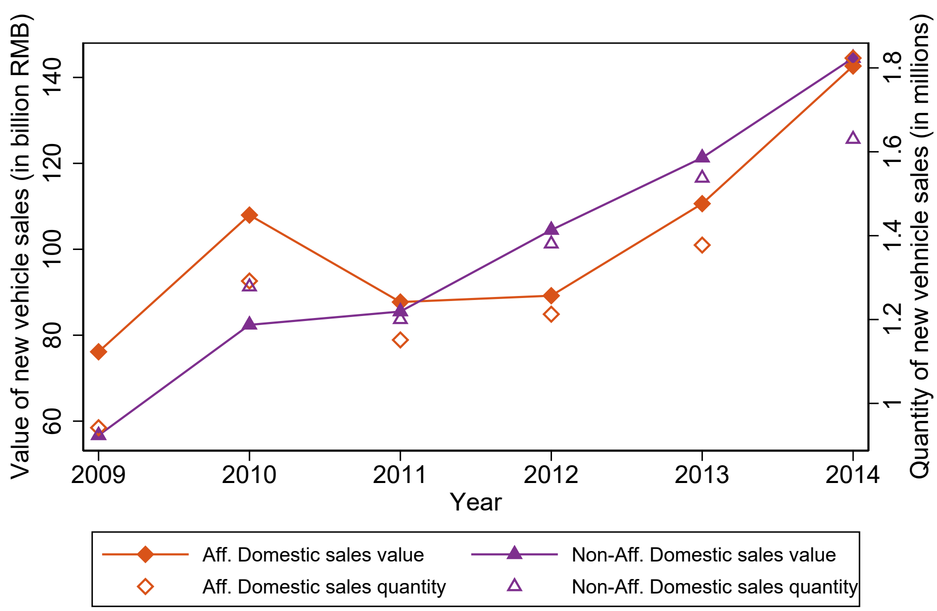

*Notes*: The figure plots the number of JVs in the Chinese auto market over time. Significant entries include: (1) 1984-1994: VW-Shanghai, VW-FAW, PSA-Dongfeng, Suzuki-Changan; (2) 1994-2000: GM-Shanghai, Honda-Guangzhou, Toyota-FAW, Suzuki-Changhe; (3) post 2000: Ford-Changan, Nissan-Dongfeng, Hyundai-Beijing,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

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

Panel A. Performance of JVs and Domestic Firms

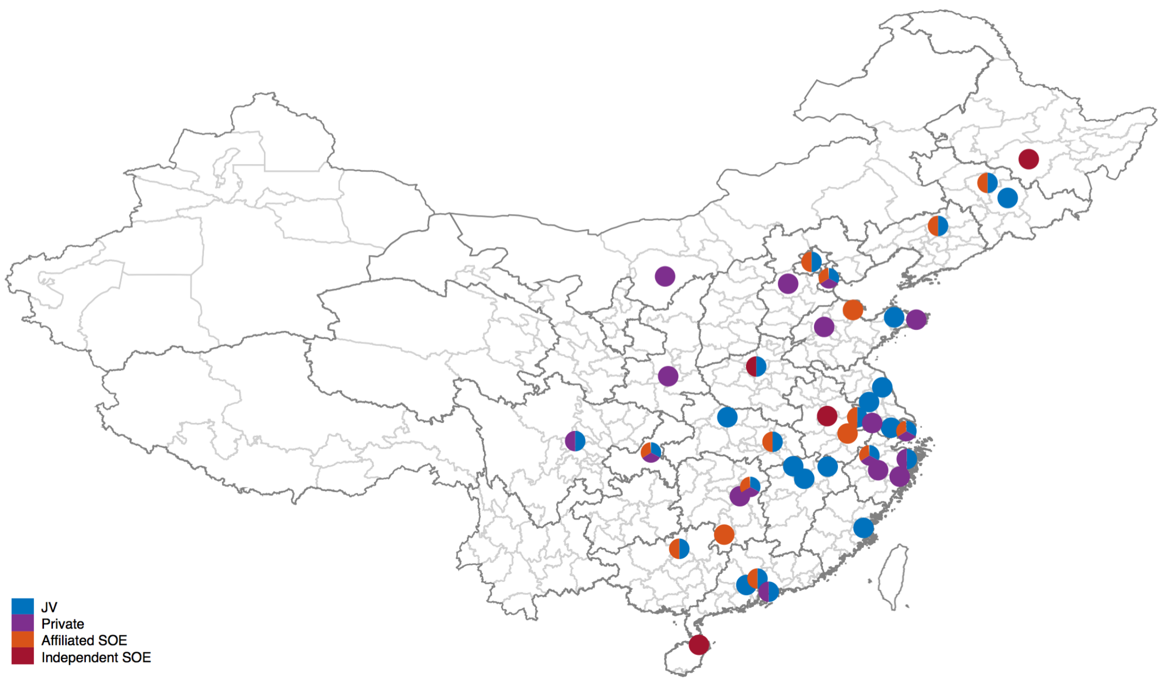



Panel B. Performance among Domestic Firms



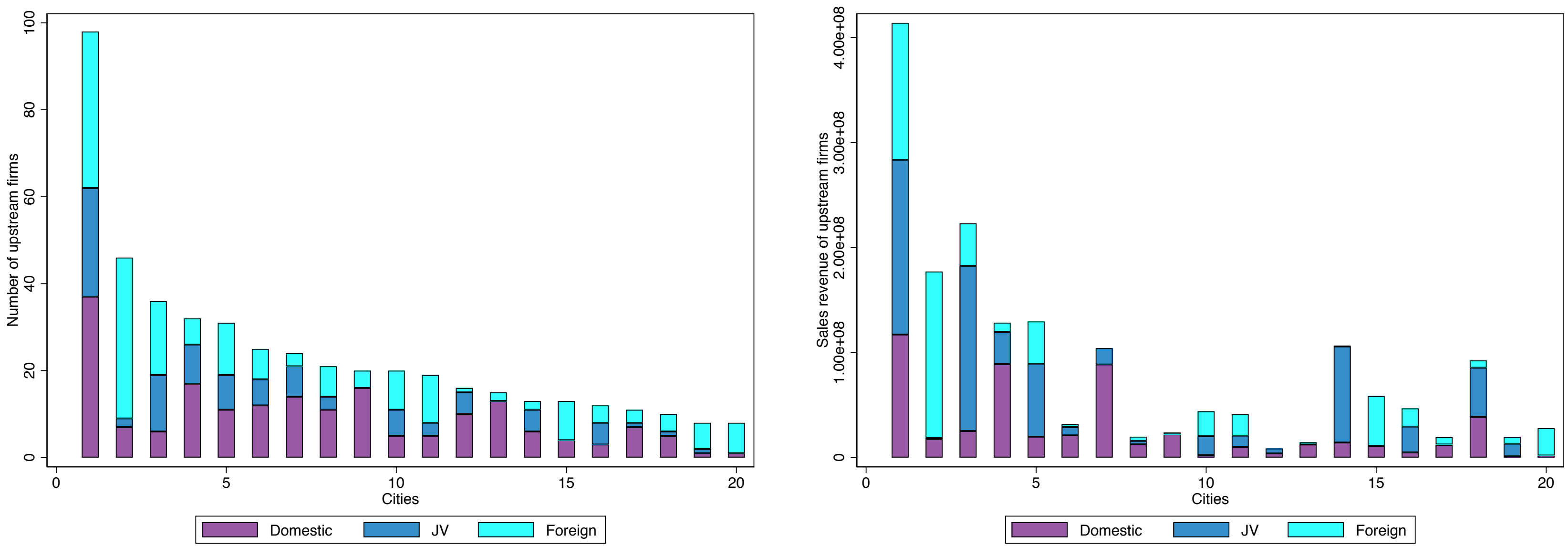

*Notes*: Sales value and quantity are calculated using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year, and does not include imported models, which account for around 3% of total sales.

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




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

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




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

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

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

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

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

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

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

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

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

Table B.4: Knowledge Spillover: Fixed Effect Models

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| JVScore | -0.002 | -0.003 | -0.003 | -0.004* | -0.003 | -0.004* |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| × SameGroup | 0.045* | 0.022 | 0.025 | 0.029 | 0.025 | 0.024 |
| | (0.025) | (0.024) | (0.022) | (0.027) | (0.025) | (0.027) |
| × SameSeg | | 0.005 | 0.003 | 0.004 | 0.001 | 0.005 |
| | | (0.005) | (0.004) | (0.005) | (0.005) | (0.004) |
| × SameGroup × SameSeg | | 0.140*** | 0.112*** | 0.159*** | 0.140*** | 0.169*** |
| | | (0.022) | (0.019) | (0.026) | (0.022) | (0.026) |
| Observations | 591280 | 591280 | 591280 | 591280 | 591280 | 591280 |
| ***Fixed Effects:*** | | | | | | |
| Firm FE | ✓ | ✓ | | | | |
| Firm-year FE | | | ✓ | | ✓ | |
| Model FE | | | | ✓ | ✓ | |
| Model-year FE | | | | | | ✓ |
| Category-year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Category-Segment FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 519,280 | 519,280 | 519,280 | 519,280 | 519,280 | 519,280 |

*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 partialing out fixed effects. All firm, model, and segment fixed effects are defined at the follower-leader pair level. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table B.5: Knowledge Spillover: Alternative Clustering of Standard Errors

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

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

Table B.6: Dynamic Spillover Effects with a Balanced Panel

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

*Notes*: This table replicates the specification in Column (2) of Table 3 using leaders' quality measures in the past. We restrict the sample to the set of models that are on the market for all six years during our sample period. Column (1) repeats the baseline regression and Column (2) uses leaders' quality measures in the previous year as the explanatory variable. Columns (3) and (4) are based on leaders' quality measures two or three years ago. Standard errors are clustered at FollowerFirm-category and LeaderFirm-category level. *** implies significance at 0.01 level, ** 0.5, * 0.1.