Quid Pro Quo, Knowledge Spillover and Industrial Quality Upgrading

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[Preliminary and Comments Welcome]

Abstract

Are *quid pro quo* (technology for market access) policies effective in facilitating knowledge spillover to developing countries? We study this question in the context of 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 along multiple dimensions of vehicle performance, we document empirical patterns consistent with knowledge spillovers through both ownership affiliation and geographical proximity: joint ventures and Chinese domestic firms with ownership or location linkage tend to specialize in similar quality dimensions. The identification primarily relies on within-product variation across quality dimensions and the results are robust to a variety of specifications. The pattern is not driven by endogenous joint-venture network formation, overlapping customer base, or learning by doing considerations. Leveraging additional micro datasets on part suppliers and worker flow, we document that supplier network and labor mobility are important channels in mediating knowledge spillovers. However, these channels are not tied to ownership affiliations. Finally, we calibrate a simple learning model and conduct policy counterfactuals to examine the role of *quid pro quo*. Our findings show that ownership affiliation facilitates learning but quality improvement is primarily driven by the other mechanisms.

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1 Introduction

Technological progress is an important engine of economic growth. To obtain technological know-how, developing countries often rely on the "*quid pro quo*" (technology for market access) policy which requires multinational firms to transfer knowledge through forming joint ventures (JVs) with domestic firms in exchange for market access. Multinational firms are often not allowed to be the majority majority shareholder of the JV.[1] The key policy rationale is to allow domestic firms to learn from foreign firms and acquire technological knowhow. However, whether *quid pro quo* is actually effective in facilitating knowledge diffusion from developed countries to developing countries is an open question.

In this paper, we study this question in the context of the Chinese automobile industry. *Quid pro quo* has been a long standing practice adopted by China in disciplining how multinational firms operate in the Chinese market. In some industrial and service sectors that China considers as strategically important, including the auto industry, the practice is manifested through joint ownership restriction with the foreign ownership strictly capped below 50%.[2] The rationale behind the policy is that the joint ownership restriction could help domestic producers learn from their foreign partners and grow into worthy competitors in the international market over time. However, multinational firms consider the technology transfer requirement as a barrier to invest and innovate in China.[3] The concern over the *quid pro quo* policy is a key stated justification behind Trump administration's decision to impose tariff on $50 billion worth of Chinese imports in early 2018.[4] Amid recent trade tensions with the US, China has promised to lift the joint ownership restriction in financial services and the automobile sector, representing a major shift from the *quid pro quo* policy in place for more than two decades.

Understanding the effectiveness of the *quid pro quo* policy in light of the complex incentives firms face could have important implications for industrial policies in developing countries and the ongoing trade discussions. Recent evidence from China suggests the *quid pro quo* practice facilitates knowledge transfer from the developed world to the developing world and enables the latter to grow (Holmes, McGrattan, and Prescott, 2015; Jiang et al., 2018). However, existing studies have focused on firm-level or industry-level aggregate outcomes such as total factor productivity and patent counts. These

[1] For example, 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. Other countries with similar policies include Brazil, India, and Malaysia.

[2] The notable sectors with the foreign ownership restriction are aircraft, automobiles, pharmaceuticals, shipbuilding, financial services, and higher education.

[3] According to China Business Climate Survey Report (2018) conducted by the American Chamber of Commerce in China, 21% of 434 companies surveyed faced pressure to transfer technology. Such pressure is most often felt in strategically important industries such as aerospace (44%) and chemicals (41%). Source: http://www.iberchina.org/files/2017/amcham_survey_2017.pdf

[4] 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 unfair technology transfer regime. Source: https://ustr.gov/sites/default/files/Section 301 FINAL.PDF.

outcome measures make it difficult to account for selection into JVs and confounding firm-level or industry-level shocks. In this paper, we leverage a unique data set on China's automobile industry with detailed quality measures along multiple dimensions for nearly the universe of vehicle models produced and sold in the country during the period of 2009 to 2015. To unpack the channels of knowledge spillovers, we further collect data on detailed plant locations, information about parts and components suppliers at the product level, and worker flow in the automobile industry. This allows us to examine the role of ownership affiliation and its interaction with geographical proximity, supplier network and labor mobility in mediating knowledge spillover.

The automobile industry is a classical industry for studying knowledge spillover and quality upgrading given the multitude of technologies embodied in the final product, including propulsion, electronics, safety, fuel efficiency, emission control, materials and most recently AI (Knittel, 2011; Aghion et al., 2016). The industry is also a fertile ground for government policies on R&D, energy and the environment. Chinese governments at both central and local levels consider the industry as a key industry for its strong linkage to a large number of upstream and downstream sectors. The industry has experienced unprecedented growth, from being virtually non-existent thirty years ago to the largest in the world in 2009. In 2017, China accounted for more than 33% of global auto production and sales. With its vast market size, China is the ground zero of international competition among auto makers and parts suppliers. All major automakers in the world have production facilities there in the form of joint ventures. The joint ownership requirement created a complicated ownership network where a foreign automaker can partner with multiple domestic automakers and vice versa. All the affiliated domestic firms are state owned enterprises. At the same time, there are non-affiliated domestic firms, mostly private, that operate independently without any foreign partner.

We compile the most comprehensive data on this industry that include: detailed product-level quality measures from JD Power, the complete joint venture network, specific plant locations, detailed information on parts and components suppliers from Marklines as well as work flows across firms from LinkedIn (China). To our knowledge, this is one of the first studies that leverages such rich data for any industry in a given country. We begin by documenting descriptive patterns of quality upgrading using the detailed quality measures from JD Power. There has been a remarkable catchup in quality among the domestic models from 2009 to 2015, both from affiliated firms and non-affiliated firms.

A multitude of demand and supply side factors could drive the quality upgrading among domestic firms. To examine the role of ownership affiliation, we leverage the multi-dimensional nature of our quality measures and exploit within-model relative quality strength across quality dimensions as the key source of variation. Intuitively, we test whether JVs and affiliated domestic brands tend to specialize in similar quality dimensions. Our identification relies on *within-product, between-quality dimension* variations, and allows for a rich set of fixed effects to account for common unobservables from both

the demand and supply sides. We find that JVs and affiliated domestic partners tend to specialize in similar quality dimensions: for models in the same vehicle segment, 14.5% of the quality improvement observed in a JV model would be transmitted to the domestic models produced by the affiliated domestic automaker. The results are robust to alternative clustering of standard errors and fixed effect controls. We rule out a host of alternative explanations including endogenous JV network formation, overlapping customer base, direct technology transfer, learning by doing and local government policies and other unobservables.

Next, to examine potential mechanisms of knowledge spillovers, we exploit the role of geography and its interaction with ownership affiliation. We find that both ownership affiliation and geographical proximity facilitate learning, and the former is not a necessary requirement for knowledge spillover. Using data on supplier network and labor mobility, we further investigate the underlying channels of knowledge spillover. Both geography and ownership affiliation lead to greater supplier overlap, and higher supplier overlap facilitates learning: in particular, supplier overlap explains 31% of the knowledge spillover via ownership affiliation. In terms of labor mobility, we document a high probability of moving to a firm of different ownership type, conditioning on moving to a new job, and 57% of movers stayed in the same city. These could explain the spillover patterns across ownership affiliation and geography.

Finally, guided by the reduced form evidence, we calibrate a simple model of knowledge diffusion to guide the policy counterfactuals. The results show that if the *quid pro quo* policy was lifted in 2009, the average quality of domestic firms would have been reduced by 12%. However, the impact of geography is much more pronounced. Overall, our findings suggest that while ownership affiliation plays a role, broad-based market mechanisms including supplier network and labor mobility have been primary channels of knowledge spillovers that drive the dramatic quality upgrading among the Chinese domestic automakers.

This paper contributes to several strands of literature. First, there has been an extensive empirical literature trying to examine whether foreign direct investment (FDI) brings productivity gains to host country firms through knowledge spillovers and the results have been mixed (Aitken and Harrison, 1999; Keller and Yeaple, 2009).[5] The literature also examines underlying channels for knowledge spillovers such as labor mobility across FDI firms to domestic firms (Balsvik, 2011; Stoyanov and Zubanov, 2012; Poole, 2013). There are at least two empirical challenges. First, the linkage between FDI and domestic firms is often characterized by an industry-level FDI employment or output share, rather than a linkage at the firm level. In addition to masking potentially important heterogeneity, this limits the ability to control for time-varying industry-level confounding factors such as emerging technologies or new

[5]Other papers in this literature include Haddad and Harrison (1993); Javorcik (2004); Haskel, Pereira, and Slaughter (2007); Blalock and Gertler (2008); Kosov (2010); Havranek and Irsova (2011); Gorodnichenko, Svejnar, and Terrell (2014); 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.

practices that could affect productivity. Second, FDI could also bring competition and affecting the performance of host country firms, making it challenging to isolate the impact from knowledge spillovers through TFP measures. We contribute to the literature by focusing on a particular industry where we have precise measure of firm linkages through ownership affiliation, geography and supplier network. We are the first one in the literature to examine spillovers at the product level rather than at the firm or industry level.

Second, our paper relates to the growing body of work in trade and development in 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 as quality is unobserved. The international trade literature has commonly used prices or unit values as a proxy for quality but prices could be a noise measure as they are also affected by production cost and market structure. Khandelwal (2010) construct a quality index based on both prices and market shares to address. In an randomized control trials to examine the impact of exporting on firms, Atkin, Khandelwal, and Osman (2017) collect multiple dimensions of quality measures of rugs through an experience quality accessor. Our research contributes to the literature by exploiting direct multi-dimensional quality measures based on user experience at the product level.

Third, 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 long-standing but controversial *quid pro quo* policy in mediating knowledge diffusion and quality upgrading and investigate the underlying mechanisms behind the policy effect. Holmes, McGrattan, and Prescott (2015) uses a calibrated dynamic general equilibrium model to simulate the impact of *quid pro quo* on firm innovation and social welfare for China and other countries while our study focuses on the role of the policy in facilitating knowledge spillovers based on micro-level data. A closely related study is Jiang et al. (2018) which uses the firm-level data with information on firm-to-firm links to examine the impact of forming an IJV on the performance (such as TFP and innovation) of domestic partners. Different from that study, our analysis uses product-level quality measures to examine knowledge spillovers from ownership affiliation with IJVs and other channels.

The remainder of the paper is organized as follows. Section 2 discusses the industrial background and data. Section 3 discusses the empirical strategy. Section 4 presents the main empirical results and robustness checks. Seciton 5 investigates the mechanisms. Section 6 discusses policy implications and provides supporting evidence from the upstream auto parts industry. Section 7 calibrates a learning

model to guide the counterfactual exercises. Section 8 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 as there was virtually no private vehicle ownership. The demand for private passenger vehicles began to emerge in the 1980s as household income increased. To increase production capacity, the Chinese government allowed international automakers to enter China but these firms are required to partner with domestic automakers in order to set up a production facility. The ownership share by foreign parties cannot be more than 50%. In forming the joint ventures (JVs), foreign automakers offer existing product lines sold in other markets and knowhow as equity while domestic automakers provide manufacturing facility and labor.[6] The *quid pro quo* policy is implemented in many other industries that are considered strategically important, from advance manufacturing such as aircraft and automobiles 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 the nascent industries (i.e., the infant industry argument). The second is to enhance domestic technical capabilities by allowing 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, the majority of manufacturing activities were made up by "knock-down kit" assembly; as a result, technology transfer was limited. Rather, foreign automakers used joint ventures as a strategy to avoid the high tariff of around 250% at that time.

There were also few indigenous brands before 2000. Most of the affiliated domestic firms did not have their own passenger vehicle production but rather relied on the JVs for production as shown in Figure A.1.[7] In 2004, the central government announced an explicit goal of developing indigenous brands and domestic automotive technology through supporting the establishment of new R&D facilities using tax incentives. The 2009 Automotive Adjustment and Revitalization Plan encourages mergers

[6] In 1978, China's First Ministry of Machinery, in charge of automobile production, invited major international automakers to visit China and negotiated with them on technology transfer with the goal of developing the 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 joint venture, which was a foreign concept to the Chinese hosts. The concept of joint venture as a way of attracting foreign automakers to provide technology was quickly reported to the pragmatic leader Deng Xiaoping who supported the idea, which 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.

[7] SAIC stopped producing their own brand in 1991 after their joint venture with VW became very successful.

and reorganizations of large-scale automobile manufacturing, as well as the creation of independent brands, both for export and for domestic sales. Under these government policies, affiliated domestic automakers started to launch their own brands of passenger vehicles. For example, SAIC (re)launched its first indigenous brand of passenger vehicles, Roewe, and FAW launched its first brand, Besturn, both in 2006. Many Besturn models are based on Mazda models. Dongfeng built its own assembly plants in 2007 and introduced its first model in 2009. By 2014, the affiliated domestic automakers have caught up with independent domestic firms in product offering as shown in Figure A.1.

After the turn of the century, the Chinese automobile market witnessed unprecedented growth: sales of new passenger vehicles increased from 0.85 million units in 2001 to 24.7 million in 2017, compared to 17.3 million in the US, the second largest market in the world.[8] In 2017, China alone accounts for more than 33% of the global auto production and sales. Lowering tariff also brought greater entry and competition to the market. The number of JVs increased after China's accession to WTO in 2001 (Figure A.2). By 2009, most of the major international automakers have launched JVs in China.

Figure 1 presents a snapshot of the joint venture network. 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. These two joint ventures are among the top three manufacturers in China and sold 3.3 million vehicles in 2015, with a market share of nearly 20% (Table 1). China has been GM's largest market for seven years in a row, with Buick and Cadillac among the most popular brands in China (Table A.1). 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. Finally, note that all of the affiliated domestic firms are state-owned enterprises (SOEs). The independent domestic firms (those without foreign partners) consist of both SOEs and private firms.

The Chinese automobile market is highly competitive with over 70 firms with production over 10,000 units in 2018. The top six accounted for 43% of the market share. In contrast, the US market has 15 automakers and the top six capture nearly 80% of the market. JVs have been dominating the passenger vehicle market as shown in Panel A of Figure 2. However, sales of domestic firms have also been growing over the past decade (Panel B of Figure 2). This is especially true in the SUV segment, where the market shares by domestic firms grew from 40% to 55% between 2009 and 2015. Figure 3 shows the top-selling models by ownership type. Buick Excelle (a sedan) by GM-SAIC and Haval H6 (a compact SUV) by private automaker Great Wall are the two most popular models by sales volume. Table A.1 lists the top 10 JV models and top 10 domestic models.

The *quid pro quo* policy is considered by other governments as part of China's broad industrial policies whereby the Chinese government creates unfair advantages for domestic companies. Because of

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

its emphasis on technology transfer, this policy is criticized as state-sponsored efforts to systematically pry technology from foreign companies.[9] Amid trade tensions between China and US, the Chinese government pledged to further open up its automobile market by removing the foreign ownership cap by 2022, effectively allowing foreign automakers to have solely-owned production facilities in China. Following the pledge, BMW and its domestic partner Brilliance reached an agreement in which BMW will pay Brilliance $4.1 billion for 25% stake in the joint venture to increase BMW's ownership share to 75% by 2022.[10] 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 first step in understanding the implications of removing such.

2.2 Data

Vehicle quality measures Our main data set is the annual IQS and APEAL studies conducted by JD Power between 2009 and 2015. Between April and June each year, JD power recruits subjects in over 50 cities in China and surveys their user experience about recently purchased vehicles. The survey covers most major passenger vehicle models in China, accounting for 88% of market shares in terms of sales in 2015. The average sample size for each model is around 100 respondents. The IQS study reports the number of problems experienced per 100 vehicles during the first 90 days of ownership. The survey asks 227 detailed functionalities, which are aggregated to nine quality dimensions.[11] Panel A of Table 2 reports the summary statistics of IQS subscores by year and ownership type. Independent SOEs and private firms are grouped into one category, i.e., non-affiliated domestic firms, for the rest of the analysis. The IQS scores are multiplied by negative one so a larger number implies better quality (fewer defects).[12] Two important patterns emerge. First, vehicle models from JVs have better quality than those from domestic firms in all quality dimensions in 2009 and the difference was large. Second, vehicle quality has increased across dimensions for both JVs and domestic models, but the improvement among domestic models was more significant. The number of defects per 100 vehicles decreased from 143 to 101 for JV models, from 216 to 124 for models produced by affiliated domestic firms, and from 269 to 111 for those produced by non-affiliated domestic firms.

[9] A 2011 report from the U.S. International Trade Commission (USITC) estimated American firms lost $48 billion in 2009 due to the infringement of US intellectual property rights and "indigenous innovation" policies that undermined their competitive positions. Source: https://www.usitc.gov/publications/332/pub4226.pdf.

[10] 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.

[11] These nine quality dimensions include exterior problems, the driving experience, feature/control/displays, audio/entertainment/navigation, seat problems, HVAC problems, interior problem, engine and transmission.

[12] In our empirical analysis, we stack all quality subscores of IQS and APEAL together and explore differential relative strength across different dimensions. To do so, we first standardize all the survey responses within a given subscore by stacking all model-year observations together and compute the z-score for each question. The standardized z-scores are then aggregated to the subscore level. Table A.2 reports the summary statistics for the standardized subscores.

The APEAL study elicits user satisfaction ratings over 100 specific vehicle quality attributes, which are then aggregated into subscores in ten performance dimensions.[13] Panel B of Table 2 shows summary statistics of APEAL subscores by year and ownership type.[14] These two studies capture different aspects of vehicle quality: IQS represents an objective measure of vehicle performance, closely related to the (mal)functionality of parts and components; APEAL represents a more subjective evaluation of the driving experience.[15] While JV models have better scores in IQS in all dimensions than domestic models, this was not true for APEAL. In addition, while there has been significant improvement in the IQS scores, the APEAL scores have only changed modestly and some have even decreased slightly over time. The comparison highlights that APEAL could be affected by varying expectation among different brands and changing expectations over time. 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-year, segment-score, and score-year) to capture the impact of expectations on the APEAL measures. We also perform robustness checks using IQS and APEAL scores separately and obtain very similar results.

To examine underlying channels of knowledge spillovers, we further collect data on the plant location of each model, part supplier network and work flows among firms.

Geography network Table A.3 shows a comprehensive list of vehicle plant locations and car models produced in each plant. Figure 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. We can observe a partial overlap between the ownership network and geographical network: for example, DongFeng, one of the largest affiliated SOE firm, has a domestic plant that locates in the same city, Wuhan, as one of its JVs' plant (Dongfeng-Honda); at the same time, Dongfeng also has a domestic plant in Liuzhou, which does not host any of its JVs. At the same time, Geely, a private firm without any JV affiliation, has a plant in Shanghai, which also hosts VW-Shanghai and GM-Shanghai. Our empirical analysis explores this partial overlap between ownership and geography to assess the role of each and their interactions in mediating knowledge spillovers.

Supplier network Data on supplier network is collected by Marklines through its Who Supplies Whom project. Our final sample covers 1378 distinct part suppliers, 271 vehicle parts under 31 part

[13]The ten performance dimensions are interior, exterior, storage and space, audio/entertainment/navigation, seats, heating/ventilation/air-conditioning, driving dynamics, engine/transmission, visibility and driving safety, fuel economy.

[14]There was a major change in the survey design in 2015, and the APEAL questionnaire in 2015 is not comparable to the previous years. Therefore, we exclude 2015 for the APEAL study.

[15]IQS includes questions such as "Engine doesn't start at all" (engine subscore), "Emergency/parking brake won't hold vehicle" (driving experience subscore), and "Cup holders - broken/ damaged" (interior subscore). APEAL includes questions such as "Smoothness of gearshift operation" (engine/transmission subscore), "Braking responsiveness/effort" (driving dynamics subscore), and "Interior materials convey an impression of high quality" (interior subscore).

categories, and 459 vehicle models that have been on the market between 2009 and 2015. Markline collects and updates information continuously through various formal or informal channels.[16] Since data at the annual level is sparse especially in the earlier periods of our sample, we pool information from all years to construct the supplier network. Table 3 shows basic summary statistics of the final sample. Each supplier on average supplies 2.8 parts and to 11 vehicle models, and there is a thin tail of large suppliers that cover many parts and models. On average, a model has supplier information for 39 vehicle parts. While the data is incomplete to be regarded as a census of suppliers for the Chinese auto industry, it provides valuable information on the production network and plausibly captures the major suppliers for each model.

Worker turnover To study labor mobility, we scrape data on employment and work 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 JV 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 users in a province and the provincial automobile production in 2018 is 0.89. The top two provinces with the largest auto production, Guangzhou and Shanghai, also have the largest number of users in our data. The data allows us to examine the patterns of worker flows across firms and relate that to knowledge spillovers.

Household vehicle ownership survey Finally, we complement the above data with a large national household-level ownership survey conducted annually by China National Information Center from 2009 to 2015. Each household in the survey reports the vehicle purchased and top alternative model considered. We use households' choices to assess whether similarity between JVs and affiliated SOEs in quality ratings could be explained by shared customer base.

2.3 Descriptive Patterns of Quality Upgrading

We begin by documenting descriptive patterns of quality upgrading based on multiple quality dimensions across ownership type. As discussed above, IQS represents a more objective measure of vehicle quality whereas APEAL scores, measuring consumer satisfaction, may evolve over time as consumers become more knowledgeable about quality. Therefore, to shed light on the time dynamics of quality improvement, we rely on IQS scores. The first graph of Figure 5 shows dramatic improvement in the

[16] Markline collects Who Supplies Whom information in a number of different ways. Some information is collected directly from the supplier company or the downstream assembly firm. Some is collected from press releases and news articles. Some is obtained from vehicle teardowns where supplier information is retrieved from the label or stamp on the vehicle part. Information is not collected when the company declines to provide it, or when the information is protected by NDA or other legal agreements. The data is continually updated as new information is gathered, and historical data is added to the old models.

overall IQS score, summed across all nine quality dimensions, for JVs, affiliated SOEs, and non-affiliated domestic automakers. In 2009, JVs have significantly higher IQS score (fewer defects) than the other two types while non-affiliated domestic automakers have the lowest. By 2015, the overall IQS score of the domestic models has largely converged to that of the JVs'. We also observe similar convergence pattern when we zoom into various subscores of IQS, for example engine and transmission and features, controls and display as shown in the second and third graphs of Figure 5.

A key challenge in isolating the effect of ownership affiliation on quality upgrading of domestic automakers is to control for confounding factors from both the demand and supply sides. As income rises and consumer demand for quality increases, domestic automakers, regardless of whether they are affiliated with foreign automakers or not, have incentives to improve quality to attract consumers. In addition, competition in the Chinese market has intensified over time with many entrants of firms and products as discussed above. This also puts more pressure on automakers to improve vehicle quality.

Our identification strategy leverages the multi-dimensional nature of our quality measures and exploits within-model relative strength across quality dimensions as the key source of variation. Figure 6 illustrates the identification strategy. Consider two models from two JVs (Brilliance-BMW and Dongfeng-Nissan) and two domestic models from the affiliated domestic automakers (Brilliance and Dongfeng). The JV model from Brilliance-BMW is relatively stronger in engine but weaker in fuel economy compared to the model from Dongfeng-Nissan. We observe the same relative strength among the two domestic models. In other words, our empirical analysis examines whether an improvement in the relative strength in a JV model corresponds to an improvement in the same quality dimension in the domestic models by the affiliated domestic firm, which we take as evidence of knowledge diffusion.

Figure 7 describes variations in relative strength among the JVs (after partialling out model and subscore-segment fixed effects) along three vehicle performance dimensions measured in APEAL, namely driving dynamics, engine and fuel efficiency. The plots show that firms have different strength across different quality dimensions. For example, models from VW-FAW and Hyundai-BAIC have better driving dynamics than others. VW-FAW and MBW-Brilliance have better scores in engine but models from Nissan-Dongfeng have better scores in fuel efficiency. This is consistent with the example shown in Figure 6 that German brands tend to focus on engine performance while Japanese brands are more fuel efficient.

We acknowledge that our framework does not allow us to identify the industry-wide spillovers, which can be confounded by industry-wide trends in quality improvement for example driven by the R&D investment of all domestic firms. This challenge is common to the literature. In addition, our framework is not able to identify the spillovers that uniformly benefit all quality dimensions of a given model given that we control for model fixed effects in order to address demand- and supply-side unobservables. An ideal variation for identification of knowledge spillovers would be exogenous entry of JVs which then

change the quality of affiliated domestic firms depending on the relative quality strength of the JVs. We do not have this type of variation as all JVs were established before our sample period.

3 Empirical Strategy

The goal of the empirical analysis is to study knowledge spillovers among automakers, from JVs (i.e., leaders) to domestic firms (e.g., followers), and factors that could mediate such spillover patterns. By leveraging the patterns of relative strength between the leaders and followers across quality dimensions, we aim to identify the causal impact of leaders' quality improvement on followers. In our analysis below, we first demean the quality scores by model-year (e.g., Brilliance-BMW 3 series in 2015), segment-score (e.g., the engine scores for compact sedans), and score-year (e.g., fuel economy scores in 2015).[17] The demeaning removes quality improvement affected by common unobservables from both the demand and supply sides. Specifically, the demeaning by model-year removes the common baseline quality level across all subscores of a model, for example, quality improvement in all dimensions due to a model redesign. Therefore, identification relies on between-subscore variation within the same model. The demeaning by segment-score captures unobservables that are specific to each vehicle segment and subscore. For example, vehicles in the luxury segment may commonly adopt certain technologies (such as lane change assist and blind spot assist that affect vehicle safety subscore) that other segments do not often use. The demeaning by score-year controls for subscore-specific time trends such as industry-wide improvement in the powertrain or the navigation systems over time.

In constructing follower-leader pairs, it is not clear a priori who the leaders for a given leader are given the complicated ownership network shown in Figure 1. In addition, our quality measures are at the vehicle model level and each automaker produces multiple models. Our empirical analysis starts with the most broad definition of leaders and gradually narrow down the definition using the empirical results as our guidance. In particular, we construct the follower-leader pairs by defining a follower as a vehicle model from a domestic automaker (either affiliated or non-affiliated) and a leader as a JV model in the same year. The nine dimensions (subscores) of IQS and ten dimensions of APEAL are standardized and stacked. The unit of observation is a follower-leader pair by subscore by year and the sample size is 585,523. There are 12,634 distinct pairs of follower-leaders with the average duration of 2.5 years for a given pair.

Denote i as the index for a domestic (or follower) model and j for a JV (or leader) model, k for a subscore (e.g., IQS score on engine), and t for year, we estimate the following equation:

$$\widetilde{\text{DMScore}}_{ijkt} = \alpha + \beta_0 \widetilde{\text{JVScore}}_{ijkt} + \widetilde{\text{JVScore}}_{ijkt} \times \text{Z}_{ij}\beta_1 + \epsilon_{ijkt} \tag{1}$$

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

DMScore_{ijkt} and JVscore_{ijkt} are demeaned IQS or APPEAL subscore k for domestic and JV models associated with the pair ij in year t. Z_{ij} is a vector of variables associated with the pair ij such as whether the pair are produced by affiliated automakers (i.e., a SOE and its affiliated JVs) or whether i and j belong to the same vehicle segment. This vector of variables allows us to investigate the scopes and channels of knowledge spillovers.

The identification of β_0 and β_1 relies on two sources of variation: the cross-sectional association in relative strength (or weakness), and contemporaneous co-movement in quality (net of overall time trend). For example, German brands such as BMW, Mercedez Benz and Volkswagen are often associated with high quality scores in engine, driving dynamics and safety dimensions. If vehicle models produced by affiliated domestic automakers exhibit high scores in these same dimensions relative to other categories, we take this as an indication of knowledge spillovers. In addition, learning could be manifested in temporal co-movement between follower and leader models in the same quality dimension.

Our empirical framework represents a significant departure from the literature on knowledge spillovers from FDI or JV to domestic firms, which has largely used firms-level panel data to construct a single index such as patent count or TFP (Aitken and Harrison, 1999; Holmes, McGrattan, and Prescott, 2015; Jiang et al., 2018). That is, the literature mainly relies on variations at the firm level while controlling for standard panel fixed effects. By focusing on different dimensions of quality measures *within* firm-product, our analysis explores a much finer level of variation and allows us to control for time-varying unobservables at the product level. This includes time-varying unobservables (e.g., demand and supply shocks) that could lead to the simultaneous usage of certain technology or parts.

The remaining identification threat is pair-subscore level common shocks. One candidate is selection in JV formation. For example, to the extent that domestic automakers choose foreign automakers of similar or different quality strength to form JVs, the selection could lead to overestimation or underestimation of knowledge spillovers. To address this concern, in one of the robustness checks, we control for model-subscore fixed effects to absorb any time-invariant common strength (or weakness) among follower-leader pairs. Thus, the identification of the key parameters relies only on temporal co-movement in quality measures of the pairs. The temporal variation is likely to be exogenous to JV formation which occurred long before most the domestic models were introduced as shown in Figures A.1 and Figure A.2. We discuss this and other alternative explanations in Section 4.4.

4 Results on Knowledge Spillovers

4.1 Identifying Relative Strength among JVs

We start by analyzing the core strength among JVs using the same framework as in Equation (1). The key difference is to generate follower-leader pairs only from models produced by JVs. For each pair of

JV models, we randomly assign one as the leader and one as the follower. This exercise serves as a proof of concept for our spillover analysis. If the framework is capable of identifying the core strength among different JVs in the form of association in various quality dimensions between follower-leader pairs within the same JV firm, we can use the same framework to examine similarity in relative quality strength between JV models and domestics models. We estimate the following equation:

$$\widetilde{\text{FollowerScore}}_{ijkt} = \alpha + \beta_0 \widetilde{\text{LeaderScore}}_{ijkt} + + \beta_1 \widetilde{\text{LeaderScore}}_{ijkt} \times \text{SameFirm}_{ij} + \epsilon_{ijkt}, \tag{2}$$

where the follower i and leader j are models from JVs. SameFirm is a dummy variable that equals to one if the pair are from the same JV firm.

Column (1) of Table 4 reports the results for the benchmark specification partialling out model-year, segment-score, and score-year fixed effects. The coefficient estimate on the interaction term between LeaderScore and SameFirm is positive and statistically significant. As the follower and leaders are randomly assigned, the coefficient estimate of β_0 has no causal interpretation and is meant to capture the correlation between a random pair of models. The estimate of 0.18 is economically meaningful: a reduction of 10 defects in a JV model is associated with a reduction of 1.8 defects among other models by the same firm. There are on average five models by each JV (see Table 2). This implies that a reduction of 10 defects in a particular dimension in a given JV model (for example due to improvement in the production process or change of part suppliers) is associated with a total reduction of 7.6 defects in the same dimension among all the other models by the same firm. This cross-model correlation in the same quality dimension within the same firm suggests that firms tend to have relative strength in some dimensions as illustrated in Figure 7. The result is robust to an alternative specification in Column (2) with model-score and score-year fixed effects. Model-score fixed effects control for the time-invariant strength of a firm in certain quality dimensions, thus the identification relies on the temporal co-movement of quality across models within a firm.

4.2 Main Results

Table 5 presents estimation results for two regressions following Equation 1. The null result on the JVScore itself in Column (1) should not be surprising given that for a vehicle model by a domestic automaker, we define its leaders to be all JV models, no matter whether they are associated with this automaker or not. SameGroup is a dummy variable that equals to one if follower-leader pair comes from a JV (e.g., Brilliance-BWW) and its affiliated domestic automaker (Brilliance). The interaction between JVScore and SameGroup dummy has a positive and statistically significant coefficient estimate, suggesting a positive association in relative quality strength between two models within the same group. The coefficient estimate is much smaller than that on the interaction between LeaderScore and SameFirm in Table 4. This comparison is intuitive and implies that the association is weaker between a JV model

and a model from an affiliated domestic firm than between two models from the same JV.

Column (2) adds two interaction terms to indicate whether a pair belongs to the same vehicle segment and in the same group. The results suggest that spillovers occur more specifically among products in the same segment and same group. This result provides an empirical guidance on the scope of spillover for our subsequent analysis. The coefficient estimate of 0.145 is economically significant: 14.5% of the quality improvement observed in a JV model would be transmitted to the domestic models in the same segment by the affiliated domestic automaker. For each JV model, there are on average 1.4 domestic models in the same segment and same group with a range of 1-3. This suggests that for a reduction of 10 defects in a JV model, there would be a reduction of about two defects among all domestic followers of that model.

Table 5 reports two-way clustered standard errors at the DomesticFirm-Score and JVFirm-Score levels. This allows for cross-sectional and temporal correlation of a given quality dimension (e.g., engine) across models in the same firm. Table A.4 reports the standard errors clustered in six different levels. The fourth specification uses two-way clustering at the Domestic-Firm and JVFirm levels. This allows for cross-score and cross-model correlation for models with the same firm. While being more flexible in the error correlation structure, it also has a much smaller number of clusters. The last two specifications allow for clustering at the firm-year level to increase the number of clusters. The key results remain intact across different levels of clustering.

Column (2) in Table 5 assumes that a follower learns equally from all affiliated JV models in the same vehicle segment. Table A.5 relaxes this assumption and examines heterogeneity in the spillovers from JV to domestic models. All the regressions focus on model pairs in the same segment. Column (1) replicates the regression in Column (2) of Table 5. Column (2) adds two interaction terms with a dummy of top three best-selling JV models in the same segment based on aggregate sales during the sample period. Column (3) examines spillovers from the JV model with the highest quality in a given segment. Overall, the evidence shows that by and large the strongest spillover occur from the JV models within the same segment and the same group. We use this to guide the remaining empirical analysis.

4.3 Robustness Checks

Our regressions so far are based on the residuals of quality measures after partialling out the model-year, score-segment, and score-year fixed effects, separately for leaders and followers. Because our design is based on the relative quality strength of followers and leaders, this method allows us to control for the baseline quality levels for the domestic models and JV models separately. Table A.6 presents three regressions with different sets of fixed effects. The first regression includes the fixed effects that are only based on the attributes of followers. That is, this regression does not control for the overall quality level of a JV model, or the quality level in a certain dimension of all JV models in a given segment as the

main specification does. The next two regressions include richer sets of fixed effects. Mathematically, these three regressions are not the same as the main specification but all of them suggest that knowledge spillovers occur in the same segment and same group.

Table A.7 presents two sets of sales weighted regressions. The first set of regressions is based on the cumulative sales of the leader model up to the current year while the second is based on the current-year sales. These regressions allow the leaders with larger sales to play a bigger role in the estimation. The key parameter estimates are very similar to those from the baseline specification without weighting.

Table A.8 reports estimation results based on leaders' quality measures in the past. The first column repeats the baseline regression and the second regression uses leaders' quality measures in the previous year as the explanatory variable. The third and fourth regressions are based on leaders' quality measures two or three years ago. The results suggest that contemporaneous spillovers appear to be the strongest. This does not mean that spillovers happen immediately in the current year. Product cycle in the automobile industry can take a decade from concept to design to finally rolling off the assembly line. Product redesign usually takes three to five years. The strong contemporaneous spillovers and the relatively quick tapering off of the lagged impact could be driven by the product cycle: domestic models may follow the product cycle of their leaders.

The relatively fast tapering off of the impact from lagged variables do not necessarily mean that learning is immediate and short-lived. Product introduction and redesign takes several years or even a decade to complete and automobile assembly itself requires integrating thousands of components into different systems (e.g., braking, emissions control, HVAC, lighting, powertrain etc.) to fit into a structure and work in harmony. The quality embodied in the final product could take several years or longer to materialize. Our analysis so far does not indicate when the spillovers occur and our analysis next on the underlying channels suggest that spillovers could occur in several stages of the production process.

4.4 Alternative Explanations

We interpret the association in relative quality strength between the domestic and JV models as evidence of knowledge spillovers from JVs to domestic automakers. Before we examine the underlying channels of spillovers, we address several alternative explanations for this finding.

Endogenous JV formation The first one is the concern over endogenous JV formation. 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 spillovers through ownership. On the other hand, if foreign firms choose to partner with domestic firms

with similar quality strength, it would bias the estimates upward.

We address this concern in two ways. First, as discussed in Section 2.1, most major JVs in the Chinese auto industry were formed between 1980s and the early 2000s, a period when domestic firms had very limited technological capacity and most did not have their own indigenous passenger vehicle brands (Figure A.1). Thus, it was difficult for the foreign firms to predict the weakness/strength of the potential Chinese partners decades later, let alone to base their partnership decisions on those predictions. To formally gauge the importance of the selection effect, Column (1) in Table 6 presents regression results excluding JVs formed after 1999. The estimated spillover among the follower-leader pairs in the same segment and same group is about 50% larger than that in the baseline specification. The spillovers are much smaller for the JVs formed between 2000 and 2004, suggesting that learning could take time to happen. Second, to control for the initial (either negative or positive) correlation between quality measures in follower-leader pairs due to strategic considerations in the JV formation stage, we remove model-score fixed effects in Table 7. This specification relies on temporal co-movement in quality measures among the follower-leader pairs. The key findings still hold.

Overlapping customer base The second concern is that the JV models and the domestic models by the affiliated automakers could be designed to appeal to the same customer base, leading to positive correlation in relative product quality.

We explore the observed household choices in the household survey data to see the extent to which JVs and domestic automakers overlap in customer base. We estimate the following equation:

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

The sample consists of all pairwise combinations of models in each year in our household choice data. ij indicates a pair of models i and j, and t indicates year. $\text{TopTwoChoices}_{ijt}$ counts the number of times the pair is listed as the top two choices by some households. A larger number suggests that the pair shares a more similar customer base. The key regressor is a dummy variable that takes value one if models i and j belong to an affiliated pair of JV and domestic automakers in the same group. We include a list of controls such as dummies for same vehicle segment, same ownership type, as well as distance in several vehicle attributes, reflecting distance in the product space. Table 8 reveals that a pair of models by a JV and a domestic automaker in the same group is *not* more likely to attract similar customers than a random pair of models after controlling for other factors. Observationally, models produced by JVs and domestic automakers compete in different consumer segments. JV models are considerably more expensive and target wealthier households. Therefore, association in the relative strength of various quality dimensions is unlikely to be driven by common demand-side factors.

One might still be concerned that even if JV and domestic models are targeting different consumer

groups, consumer perception of quality strength might be affected by the affiliation. For example, consumers may perceive Brilliance models have 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 largely reflects consumer attitude and perception of different quality dimensions, the IQS survey is designed to be more objective as it asks respondents to report the number of defects. Columns (2) and (3) in Table 9 show that the estimates are very close between IQS and APEAL.

Direct technology transfer The third alternative explanation is that knowledge spillovers observed in the data could be driven by direct technology transfers through market transactions. This is an unsolved challenge in the broad literature on studying the impact of FDI on knowledge spillovers due to the lack of data on complete market transactions (Keller, 2004). The distinction between spillovers (an externality) and transfers through market transactions is important for policy implication. The literature typically relies on across-industry over-time variations in FDI intensity. However, one could argue that the identified spillover could be driven by unobserved market transactions.

To address this concern, we obtain data on all patent transfers among the JVs and domestic automakers during 2009 to 2016 from the National Intellectual Property Administration (i.e., the Chinese Patent Office). There are two types of transfers: patent licensing and patent assignment. The former is a 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.

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 affiliated firms, i.e., from a parent company to a subsidiary company or vise versa, 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 finding of limited direct transfer is consistent with the findings in (Holmes, McGrattan, and Prescott, 2015) which shows that JVs in China file a very 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.

Learning by doing The results so far point to knowledge spillovers from JVs to domestic automakers. However, where does the knowhow of the JVs come from? One might argue that the knowhow could come from learning by doing by the JVs, which then passed on to the domestic partner. That is, there

may not be any technology transfer from foreign automakers related to the *quid pro quo* policy. Table 10 examines the intensity of spillover focusing on affiliated pairs in the same segment and same group. Column (2) shows that the spillover is weaker if the total JV sales is larger. This is not consistent with a story of pure learning by doing. The spillover is stronger for followers that have larger sales. This could be due to the fact that domestic models that learn more from the JV models are better products. Column (3) can be viewed as a falsification test where we look at non-affiliated pairs. The coefficient estimates are zero for those interactions.

The ownership requirement was put in place specifically to facilitate knowledge transfer from foreign automakers to JVs. As mentioned in Section 2.1, in forming the JVs, foreign automakers offer existing product lines sold in other markets and knowhow as equity while domestic automakers provide manufacturing facility and labor. This is a standard practice in the industry.

Local government policies and other unobservables Barwick, Cao, and Li (2017) demonstrates that local governments use preferential policies to help local automakers compete against other non-local automakers. To the extent that affiliated SOEs and JVs tend to locate in the same cities, one might worry that these subsidies could lead to JVs and domestic automakers to specialize in similar quality dimensions. However, most of the subsidies are not tied to particular features or dimensions but are rather tied to the local production status.[18]

Similarly, there could be other time-varying unobservables that push the JVs and domestic automakers to specialize in similar quality dimensions. For example, there could be joint decisions in input purchases, workforce training and marketing activities due to economies of scale and some of these could affect certain but not all quality dimensions. Our discussion with industry experts suggests that these joint activities are not common. JVs and affiliated domestic automakers are separate business entities with their own objectives. In addition, many domestic models appear much later than the JV models, which limits the scope for such joint activities.

5 Mechanisms of Knowledge Spillovers

The production of a vehicle includes interrelated stages from product planning (e.g., market analysis), design and engineering (e.g., chassis, powertrain, exterior and interior), sourcing of parts of components, testing, and assembly. The whole process involves complex interactions of technologies, processes, and workers.[19] Knowledge spillovers could occur during all stages of the production process through

[18] An exception is the subsidy on electric vehicles (EVs). The subsidy amount is tied to the range of EVs with the purpose of promoting battery technology. EVs account for less than one percent of the market share before 2017 and we do not include them in our analysis.

[19] "That shiny new car or truck in your local dealer's showroom is more than just hardware, more than just metal, plastic, glass and rubber bolted together. The reason it exists is the result of a complex interaction of people, politics, and

many different channels—deliberate actions of the partners, flow of know-how through shared parts suppliers, communication among workers, etc. In this section, we first investigate the role of geography in mediating knowledge spillovers and then zoom into two potential underlying channels, namely supplier network and labor mobility.

5.1 The Role of Geography

The strong role of geographical proximity in knowledge spillovers has long been emphasized in the literature (Krugman, 1991; Jaffe, Trajtenberg, and Henderson, 1993; Audretsch and Feldman, 1996; Keller, 2002). The literature documents that physical proximity and concentration of people and firms facilitate the exchange of ideas and promote innovation. We collect information on the location of all auto plants and the associated models produced in each plant. Figure 4 shows a map of all automobile plant locations in China in 2015. As discussed in Section 2.2, the ownership network partially overlaps with geographical network.

To examine the role of geography in promoting spatially-mediated knowledge spillovers, we interact the ownership dummies with the location dummies in Table 11. Column (1) focuses on follower-leader pairs in the same segment. The results suggest that both geographical proximity and ownership affiliation facilitate knowledge spillovers. The strongest spillover occurs among the pairs within the same group and in the same city: 20% of the quality improvement in a leader model would be transmitted to the follower models for the pairs in the same segment, same group, and same city.

At the same time, a follower model could learn from a leader model that is located in the same city even *without* ownership affiliation. The estimated coefficient is 0.144, positive and statistically significant at 10 percent level. This suggests that ownership affiliation is not a necessary requirement for knowledge spillover.

Column (2) includes all the follower-leader pairs and allows us to examine the spillover across pairs in different segments. The coefficient estimates imply that spillovers exist among pairs in the same city regardless whether the products are in the same segment or in the same group. While ownership affiliation leads to spillovers among products only in the same segment, spillovers through geographical proximity appear to be more general and stronger. Next, we examine the two potential channels of impacts that could manifest through ownership affiliation and geography: supplier network and labor mobility.

5.2 Supplier Network

Knowledge spillovers could occur through the shared supplier network. Quality of parts and components are key determinants of a vehicle's quality. A vehicle has about 30,000 distinctive parts on average and

process." (Angus McKenzie, Motor Trend)

automakers source most of them from a large and complex supplier network with nearly 10,000 suppliers in China.[20] From sourcing the parts mostly from foreign part suppliers in the 1990's and early 2000's to mostly sourcing from domestic part suppliers in recent years, the presence of the JVs has been argued to have helped and incentivized domestic part suppliers to improve their product quality, which then also benefit domestic automakers.[21] The sourcing decisions of the JVs may provide valuable information to the domestic partners and help the latter to identify good parts and components suppliers.

To examine the contribution of supplier network to knowledge spillovers between JVs and domestic automakers, we proceed in two steps. First, we quantify the effects of ownership affiliation and geographical proximity on the extent of suppler overlap. We take our supplier data and create a sample consisting of all pairwise combinations of JV-domestic models. To examine whether affiliated JV-SOE pairs or pairs in the same city disproportionally share more common suppliers, we run the following OLS regression:

$$\text{SupplierOverlap}_{ij} = \alpha + \beta_1 \text{SameGroup}_{ij} + \beta_2 \text{SameCity}_{ij} + \varepsilon_{ij} \tag{4}$$

where ij represents a pair of models. $\text{SupplierOverlap}_{ij}$ counts the number of common part suppliers shared by i and j. SameGroup_{ij} is a dummy that equals to one if the pair consists of models from an affiliated JV and domestic automaker. SameCity_{ij} is a dummy that equals to one if the pair consists of models from a JV and a domestic automaker in the same city.

Results are shown in Table 12. Both ownership and geographical linkages have a sizable impact on supplier overlap. Column (1) shows that a JV and affiliated SOE on average have one more shared part supplier in common compared to a non-affiliated pair. This represents 30% increase of the average overlap (3.19). Similarly, geographical proximity also leads to significantly greater supplier overlap.

In the second step, we examine the impact of supplier overlap on relative quality strength. The idea is that part of the similarity in relative quality along different dimensions could be driven by supplier quality. For each model pair, we compute the Szymkiewicz-Simpson overlap ratio, which equals to the number of common part suppliers divided by the distinct numbers of suppliers of the pair (smaller number of the two). We standardize the overlap ratio across pair-year observations and interact the z-score with the leader's score and segment-group dummies. Table 13 reports results, focusing on JV-domestic pairs in the same vehicle segment. Panel A shows that a larger supplier overlap is indeed associated with stronger knowledge spillovers via ownership affiliation. Using estimates from Column

[20] This number includes all tiers of parts and components suppliers. The data from Marklines primarily contains the first-tier suppliers.

[21] The 1994 Auto Policy requires that all joint ventures must localize at least 40% of their parts and components. This has led to the development of the upstream industry. For example, in 1994, the localization rate for the VW Jetta was only 24 percent but by 2000, it had reached 84 percent (Gallagher, 2003). The local content requirement was officially lifted after China entered into the WTO in 2001.

(1) and (2), a simple back-of-the-envelope calculation implies that supplier overlap explains 31% of the knowledge spillovers via ownership affiliation.[22] Panel B shows that supplier network also plays an important role for the impact of geography, explaining about 42% of the spillovers via geography.

5.3 Labor Mobility

The mobility of workers, especially skilled worker as knowledge carriers, can lead to knowledge spillovers across firms. The importance of labor mobility in knowledge spillovers has been studied both theoretically and empirically (Fosfuri, Motta, and Rønde, 2001; Kim and Marschke, 2005; Møen, 2005; Stoyanov and Zubanov, 2012; Castillo et al., 2016; Serafinelli, 2019). Recent empirical studies have documented this as a channel of knowledge spillovers from multinational firms to domestic firms (Balsvik, 2011; Stoyanov and Zubanov, 2012; Poole, 2013). Before foreign automakers entered China, passenger vehicle production was nearly non-existent and the labor force in the auto industry was small and not well trained. JVs provide a training ground in both engineering and managerial knowhow for the labor force. As the labor force becomes more mobile, management and skilled workers flow between JVs and domestic automakers. Among the employees in domestic automakers, many high-level management and skilled workers had gained valuable experience in the JVs. These workers joined domestic automakers in order to further their career as these automakers often entrust them with higher-level positions. The movement of these knowledge carriers leads to the flow of knowledge in various dimensions from engineering capabilities to logistic and managerial practices.

We analyze labor mobility among automakers by ownership type using data from LinkedIn (China). The data contains 52,898 LinkedIn users who have worked in 60 JV and domestic firms. By examining the work history in the user profiles, we can track workers' turnover over time. Table 14 presents the transition matrix of worker mobility by ownership type. So far, we have cleaned 10,000 (out of 52,898) user profiles and among these users, at least 16 percent of them has changed employers. Panel A shows the turnover for all 1,632 workers who have ever changed employers while Panel B shows that for 930 skilled workers. There are two key takeaways. First, conditioning on moving to a new job, there is a high probability of moving to a firm of different ownership type. For example, for a worker in a JV, she has a 41 percent chance of moving to another JV, 35 percent chance of moving to an non-affiliated domestic firm and 24 percent chance of moving to an affiliated domestic firm. Among the 24 percent moving from a JV to an affiliated domestic firm, about one-third (31 out of 91) moved to a firm affiliated with the given JV. Second, the skilled workers, no matter where they initially worked, prefer to move to a non-affiliated domestic firm than to a firm of other ownership types.

In terms of the spatial pattern of labor mobility, 57 percent of movers stayed in the same city

[22] The average supplier overlap ratio between JV-domestic models in the same group and same segment is 1.1. Therefore, supplier overlap explains $1 \times 0.043/0.145 = 31\%$ of the spillover effect within group and segment.

and 61 percent stayed in the same province. Labor mobility from JVs to non-affiliated and affiliated domestic firms could help ideas, practices and technology knowhow to flow. This channel is consistent with knowledge spillovers from JVs to not only firms in the same group but also to firms in different groups as shown in Table 11. The stronger preference for non-affiliated domestic firms among the skilled workers could reflect the strong recruiting efforts these firms undertake in order to attract top engineers and management talents. As shown in Figure 5, quality improvement in the non-affiliated firms, such as Geely and BYD, has been faster than the affiliated firms, which has contributed to their increasing market share and stronger brand image in recent years.

6 Policy Implications

The reduced form results suggest that both ownership affiliation and geographical proximity facilitate learning, and the former is not a necessary requirement for knowledge spillovers. Furthermore, the underlying mechanisms discussed in Section 5, namely supplier network and worker mobility, are broad-based and not tied to ownership affiliation per se. However, a skeptical view is that spillover can only happen with some form of *quid pro quo* in place: once a firm becomes wholly foreign owned, it could manage to silo its information and knowhow, resulting in fundamentally different diffusion patterns.

The key empirical challenge of addressing this question is the lack of variation in ownership structure in the Chinese auto industry (i.e. the counterfactual of 100% foreign ownership is never observed in this empirical setting). Like typical nationwide industrial policies, it is difficult to find exogenous subnational variations or natural experimental settings. In this section, we present two pieces of supporting evidence to speak to the policy counterfactual: first, we explore cases where a non-affiliated plant locates in a city that hosts a JV plant but none of the affiliated domestic plants. Second, we map the quality measures we have in the downstream industry to quality of the upstream suppliers and explore variations in ownership structure in the upstream industry.

6.1 Cities without Affiliated SOEs

If having an affiliated domestic partner per se is crucial in mediating knowledge diffusion, not only to the affiliated firm itself but also to other non-affiliated domestic firms, then we would expect that non-affiliated firms in places without affiliated firms would benefit less from the presence of foreign firms. As shown in Figure 4, there are cases where a city hosts only non-affiliated plants and JV plants (i.e. the blue-purple circles on the map). One example is Chengdu, which hosts a plant by a private firm, Geely, and two plants by two JVs, Toyota-FAW and VW-FAW, but without any plant by the affiliated domestic partner, FAW (Table A.3).

Exploring these cases, Table 15 considers pairs of models of non-affiliated domestic firms and JVs.

The omitted group is non-affiliated domestic-JV pairs in different cities. The key interaction dummies are whether the two models are produced in the same city and whether the city hosts any affiliated domestic plant. If anything, the spillover is larger among pairs located in cities without the JV's affiliated domestic partner, suggesting that the latter is not a necessary conduit for knowledge spillovers.

6.2 Evidence from the Upstream Auto Parts Industry

Despite the lack of ownership variation in the downstream auto assembly industry, the upstream parts and components industry features a dynamic environment with considerable variation in ownership composition across locations. Figure 8 shows the distribution of ownership types 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). The survey includes all industrial firms that are identified as being either state-owned or non-state firms with sales revenue above 5 million RMB. We identify auto parts and components firms using the 3-digit industry classification (GB/T). Figure 8 shows the breakdown of ownership type in the top 20 cities, defined in terms of total sales revenue from 2009 to 2014 (the last year of the NBS data).[23]

We leverage the variation in the upstream industry to examine whether there is any differential spillovers to domestic firms from wholly owned FDIs versus JVs. We proceed in the following steps: first, we use the IQS and Markline data to construct a measure of quality Q_{ijt} for supplier i-part j in year t. To do so, we first map all the micro-level IQS scores (covering 227 functionalities for each model) to vehicle parts and components categories. This gives us a measure of quality 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-part category, Q_{ijt}, as the average of supplier i's downstream models' IQS scores corresponding to part category j, weighted by the downstream models' sales.

In the second step, we explore city-part-level variations in supplier quality and FDI/JV intensity:

$$Q_{ijct}^{\text{Dom}} = \alpha + \beta_1 \tilde{Q}_{jct}^{\text{JV}} + \beta_2 \tilde{Q}_{jct}^{\text{Foreign}} + \lambda_{cj} + \lambda_t + \epsilon_{ijct} \tag{5}$$

The dependent variable is quality of a domestic supplier i in city t for part category j in year t. The key regressors are the average quality of JVs and wholly-owned foreign firms of the same part category j in city c in year t. To account for selection, we can control for city-part fixed effects and explore temporal variations in quality improvement.

Our final analysis sample contains 660 unique suppliers,[24] 184 unique parts belonging to 25 part

[23] There are two approaches in the literature in identifying a firm's ownership type: 1. using the registration types of firms (e.g. Yu (2015)); and 2. using the shareholder information based on the registered capital (e.g. Brandt, Van Biesebroeck, and Zhang (2012); Hsieh and Song (2015)). Because our focus is on the distinction between joint venture and sole foreign ownership, we define ownership types using the second approach. The results are robust to the alternative definition.

[24] We have 1020 suppliers with quality information (out of 1378 in MarkLine) and 660 are identified in the NBS data

categories, for 6 years (2009-2014). On average, for each supplier, we observe 2.6 parts. These upstream firms are distributed in 96 cities; of which, 21 host all three ownership types. In total, these cities have 414 firms, including 98 JVs, 150 foreign firms and 148 domestic firms. For cities without JVs or foreign firms, we define the average quality measures as zero and include dummy variables for these cases.

Table 16 shows the regression results. We consider both the simple average quality of the JV and foreign firms in a city as well as sales weighted average quality. Column (4) and (8) are our preferred specifications controlling for city-part fixed effects. Overall, the results provide little support that spillovers to domestic firms are larger from JVs than from wholly owned foreign firms. In fact, the positive impact of foreign firms appears to be larger than joint ventures when we use the sales-weighted measures of quality as shown in Column (8).

7 A Simple Model of Knowledge Spillover

We write a simple learning model where the size of the spillovers in each quality dimension is proportional to the difference between the leader's and follower's quality. In other words, the scope and speed of learning diminishes as the follower catches up on quality. Let q^k denote the quality of the follower in quality dimension k. Let $\tilde{\delta}^k = \bar{\delta} + \varepsilon^k$ denote the counterfactual quality of the follower in dimension k in the absence of knowledge spillovers. It consists of a baseline quality $\bar{\delta}$ that is common to all quality dimensions, and a dimension specific component ε^k. Similarly, a leader's quality Q^k could be decomposed into $\bar{Q}$ and μ^k, a baseline component common to all dimensions and a quality-specific comparative (dis)advantage. We classify leaders into four classes by ownership affiliation and geographical proximity: same group and same city (SS), same group and difficult city (SD), different group and same city (DS) and finally different group and different city (DD). We write (abbreviating time subscript):

$$\begin{aligned} q^k &= \tilde{\delta}^k + \rho_{SS}\sum_{i=1}^{N_{SS}}(Q_i^k - \tilde{\delta}^k) + \rho_{SD}\sum_{i=1}^{N_{SD}}(Q_i^k - \tilde{\delta}^k) + \rho_{DS}\sum_{i=1}^{N_{DS}}(Q_i^k - \tilde{\delta}^k) + \rho_{DD}\sum_{i=1}^{N_{DD}}(Q_i^k - \tilde{\delta}^k) \\ &= (\bar{\delta} + \varepsilon^k)(1 - N_{SS}\rho_{SS} - N_{SD}\rho_{SD} - N_{DS}\rho_{DS} - N_{DD}\rho_{DD}) \\ &\quad + \rho_{SS}\sum_{i=1}^{N_{SS}}\bar{Q}_i + \rho_{SD}\sum_{i=1}^{N_{SD}}\bar{Q}_i + \rho_{DS}\sum_{i=1}^{N_{DS}}\bar{Q}_i + \rho_{DD}\sum_{i=1}^{N_{DD}}\bar{Q}_i \\ &\quad + \rho_{SS}\sum_{i=1}^{N_{SS}}\mu_i^k + \rho_{SD}\sum_{i=1}^{N_{SD}}\mu_i^k + \rho_{DS}\sum_{i=1}^{N_{DS}}\mu_i^k + \rho_{DD}\sum_{i=1}^{N_{DD}}\mu_i^k \end{aligned} \tag{6}$$

where $\rho_{SS}, \rho_{SD}, \rho_{DS}$ and ρ_{DD} capture spillovers from the four different classes of leaders. The model allows a follower to benefit from multiple leaders in a given class. Let ξ^k denote the follower's residualized

with information on ownership structure.

scores in dimension k. Define $\gamma = (1 - N_{SS}\rho_{SS} - N_{SD}\rho_{SD} - N_{DS}\rho_{DS} - N_{DD}\rho_{DD})$. It follows that:

$$\xi^k = \rho_{SS} \sum_{i=1}^{N_{SS}} \mu_i^k + \rho_{SD} \sum_{i=1}^{N_{SD}} \mu_i^k + \rho_{DS} \sum_{i=1}^{N_{DS}} \mu_i^k + \rho_{DD} \sum_{i=1}^{N_{DD}} \mu_i^k + \gamma\varepsilon^k \tag{7}$$

This expression mimics our empirical framework and we use our reduced form estimates in Table 11 to calibrate the spillover parameters $\rho_{SS}, \rho_{SD}, \rho_{DS}$ and ρ_{DD}. To simulate counterfactual quality dynamics, we assume $\tilde{\delta}^k$ evolves as follows:

$$\tilde{\delta}_t^k = q_{t-1}^k + \omega_t^k \tag{8}$$

where ω_t^k represents other factors that affect quality.

We consider two counterfactual exercises: first, what would have happened to the quality of the domestic automakers if the *quid pro quo* policy was lifted in 2009 (i.e., $\rho_{SS} = \rho_{DS}$ and $\rho_{SD} = \rho_{DD}$)? Second, what would have happened if we shut down spillovers by both ownership and geographical linkages (i.e. setting all ρ's to 0)? Results are shown in Figure 9. The solid lines plot the observed average quality improvements in terms of the total IQS score for JV and domestic models. Lifting the policy reduces average quality of domestic firms by 12% during this period. Considering an overall reduction of 130 defects from 2009 to 2015 among domestic models, this is equivalent to 16 fewer reductions in vehicle defect. Having said that, the impact of geography is much more pronounced: the gap between the dotted line and the dashed line represents a 29% gap in average quality.

8 Conclusion

This study sets out to study the policy of technology transfer for market access, i.e., *quid pro quo* policy, in facilitating knowledge spillovers from developed countries to developing countries. Chinese automobile industry offers an ideal setting to study this question given the rich variation introduced by the complex cross-ownership structure and rich industry dynamics. Leveraging unique datasets on quality ratings, supplier networks, worker flow, and household surveys, we document consistent patterns of knowledge spillovers from joint ventures (JVs) to domestic automakers during our data period from 2009 to 2015. Our analysis suggests that both ownership affiliation and geographical proximity facilitate learning, and the former is not a necessary requirement for knowledge spillovers. Broad-based market mechanisms including supplier network and labor mobility have been primary channels of knowledge spillovers that drive the dramatic quality upgrading among the Chinese domestic automakers.

The recent pledge by the Chinese government to remove the foreign ownership restriction for automobile manufacturing, thus ending the *quid pro quo* policy, could have profound impacts on the industry. Our findings imply that the policy change would not significantly hinder the process of qual-

ity upgrading in the industry. 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 knowhow. Domestic automakers would face stronger pressure to innovate on their own or exit the market. Consumers welfare would hinge on the balance between product quality and market concentration under the new environment. In addition, how foreign firms' incentives to innovate and introduce technology may interact with global knowledge diffusion is an important open area for empirical research (Buera and Oberfield, 2016; Bilir and Morales, 2016). We leave these questions for future work.

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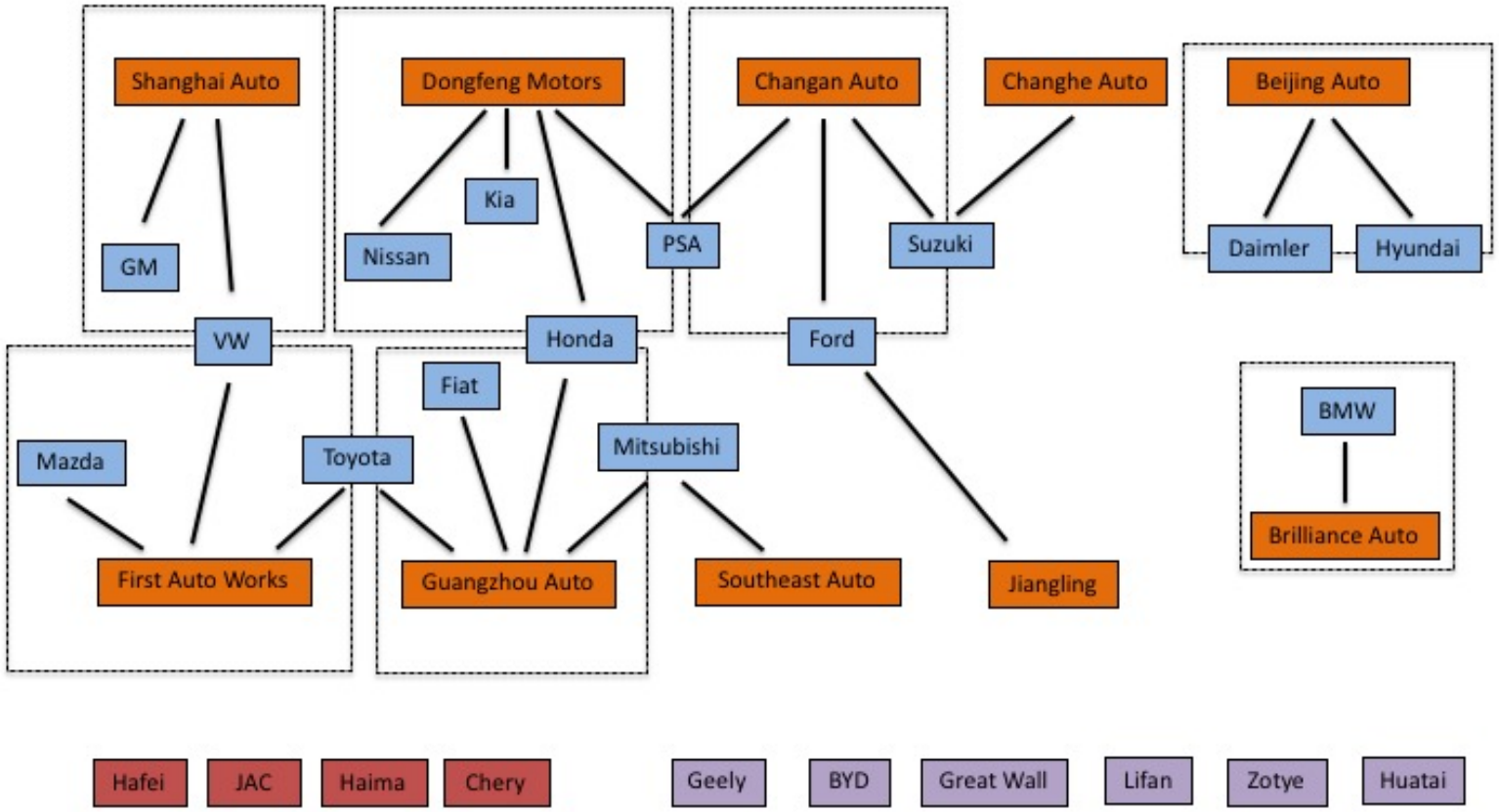
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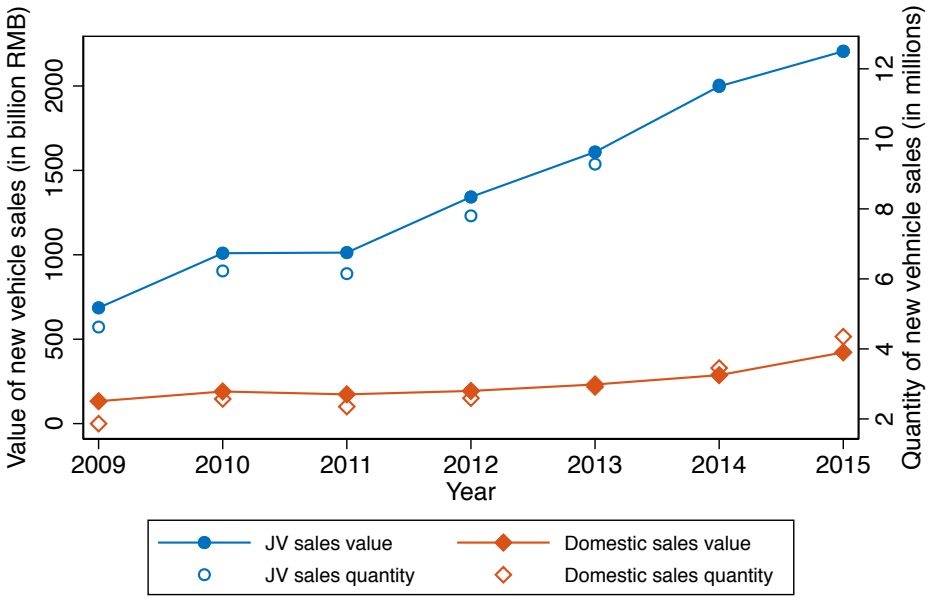
Figure 1: Joint Venture Network of the Chinese Auto Industry



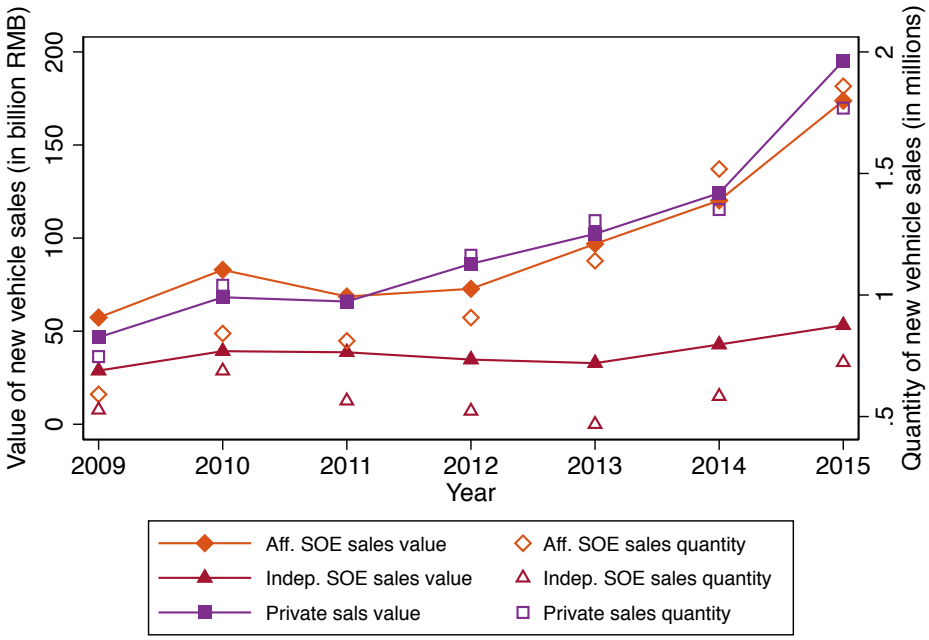
Notes: This figure is adapted from Figure 1 of Chen, Lawell, and Wang (2017). It describes the joint venture network of the Chinese auto market as of 2015. Orange boxes represent affiliated SOEs; blue boxes represent foreign partners in JVs; purple boxes represent private domestic firms; red boxes represent independent SOEs. The dashed lines indicate groups of JVs that share the same affiliated domestic SOE.

Figure 2: Growth of the Chinese Auto Industry by Ownership Type

Panel A. Performance of JVs and Domestic Firms



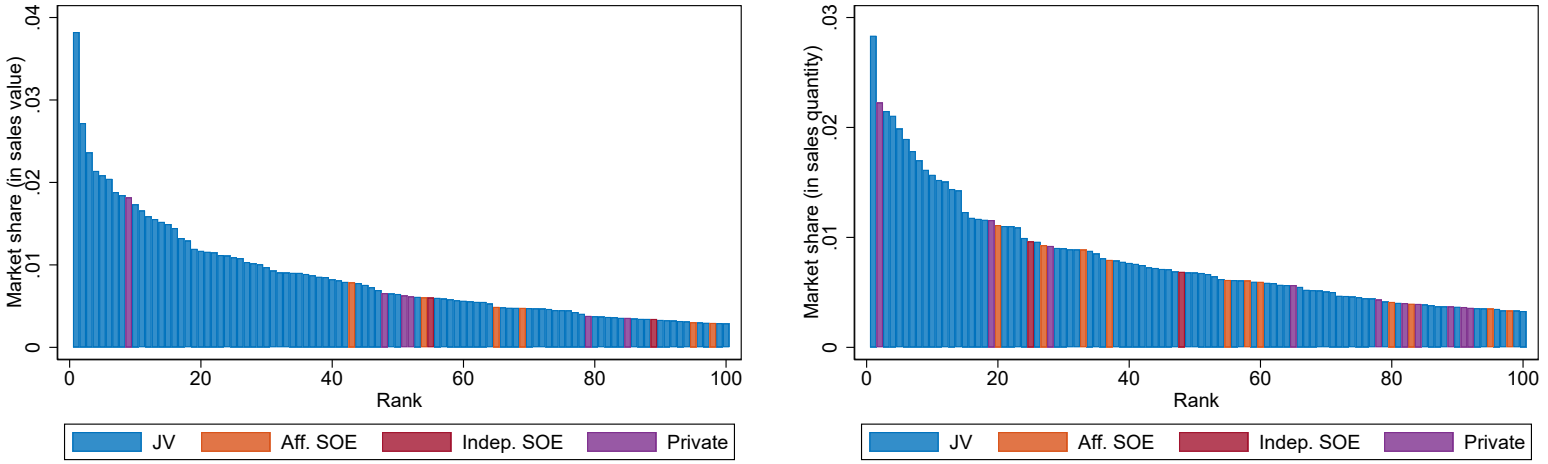
Panel B. Performance among Domestic Firms



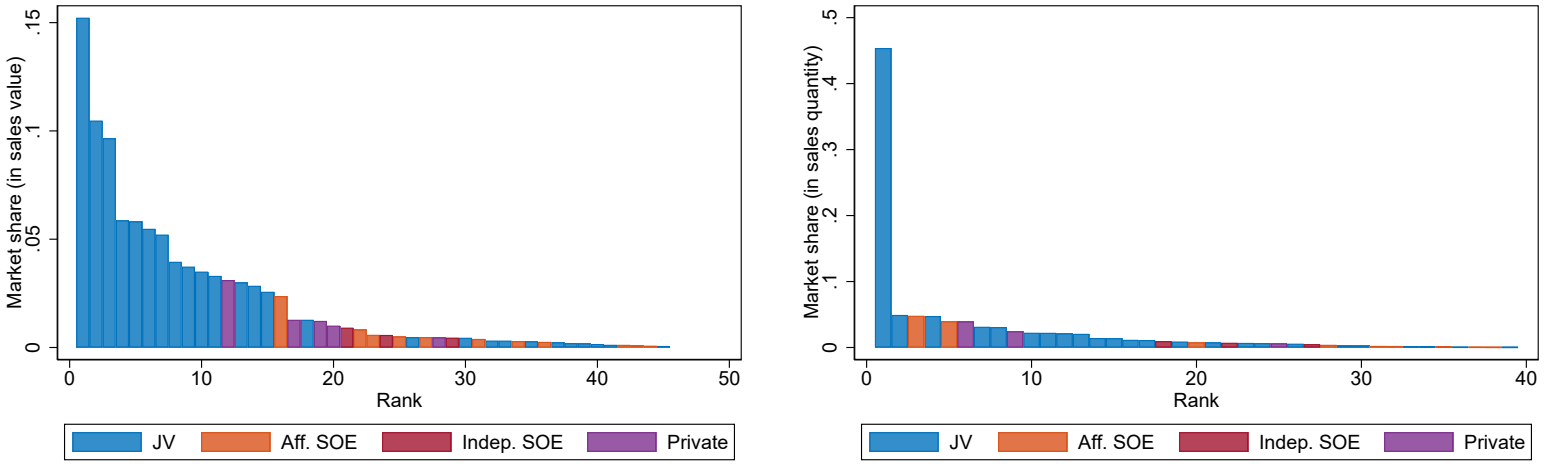
Notes: Sales value and quantity are calculated using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year, and does not include imported models, which account for around 3% of total sales.

Figure 3: Market Share of Top Firms and Models and Ownership Type

Panel A. Top 100 Models by Market Share in 2015

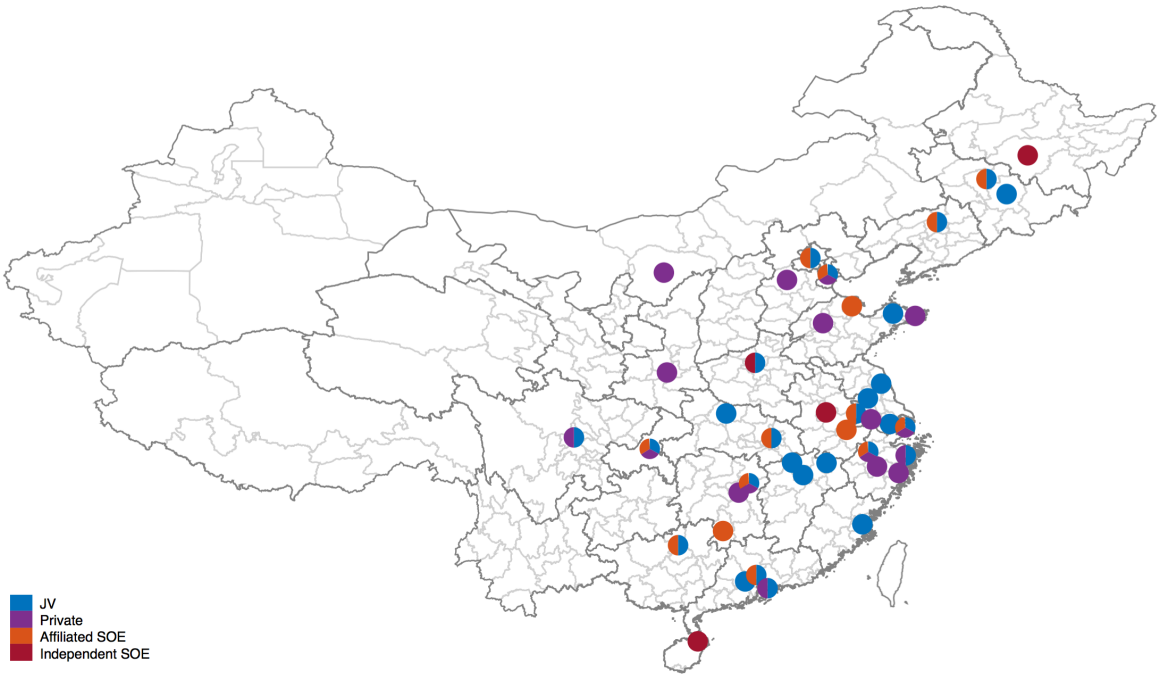


Panel B. Top Firms by Market Share in 2015



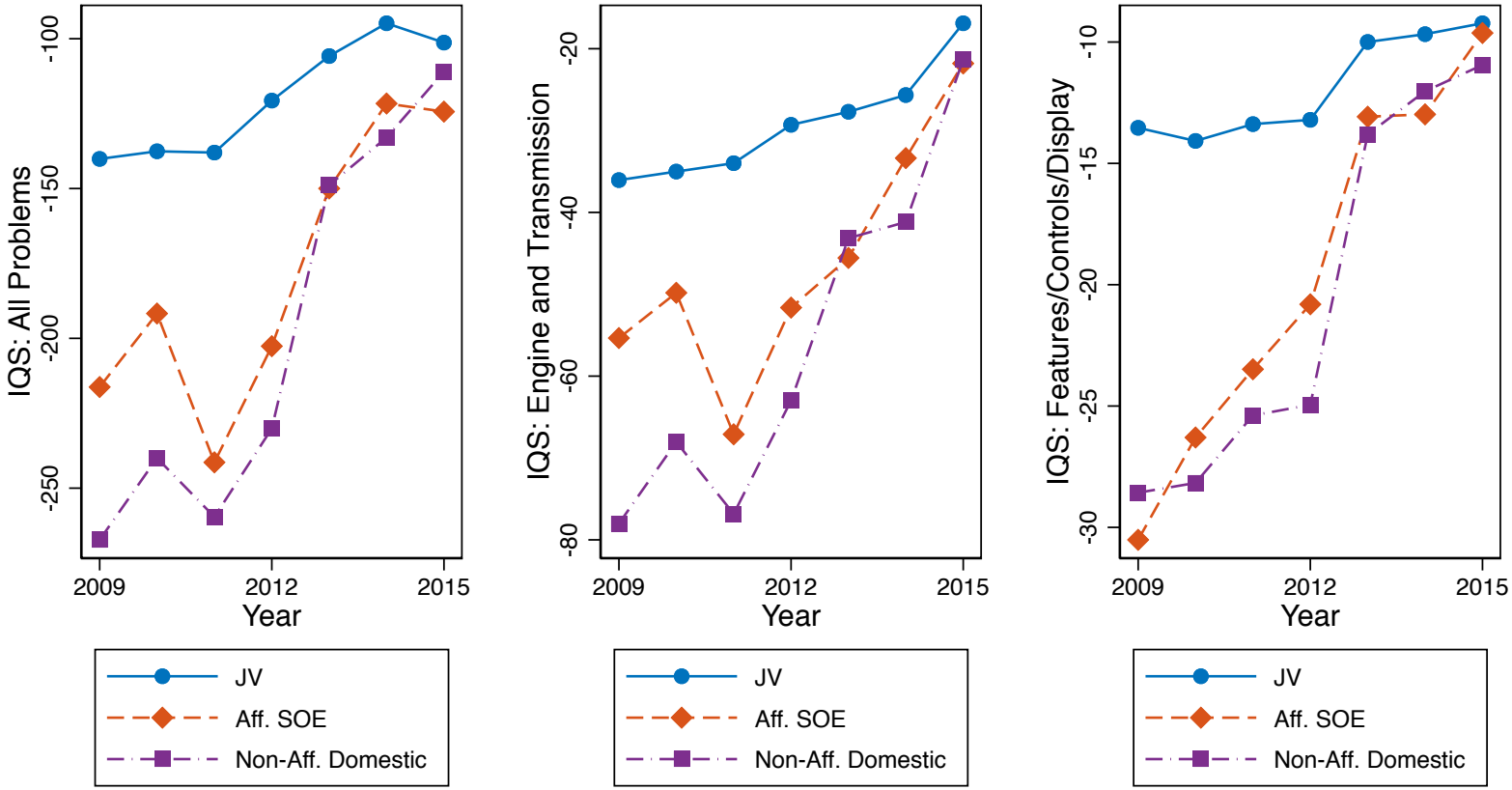
Notes: Market shares using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year, and does not include imported models, which account for around 3% of total sales.

Figure 4: Geographical Distribution of Vehicle Production Plants in China



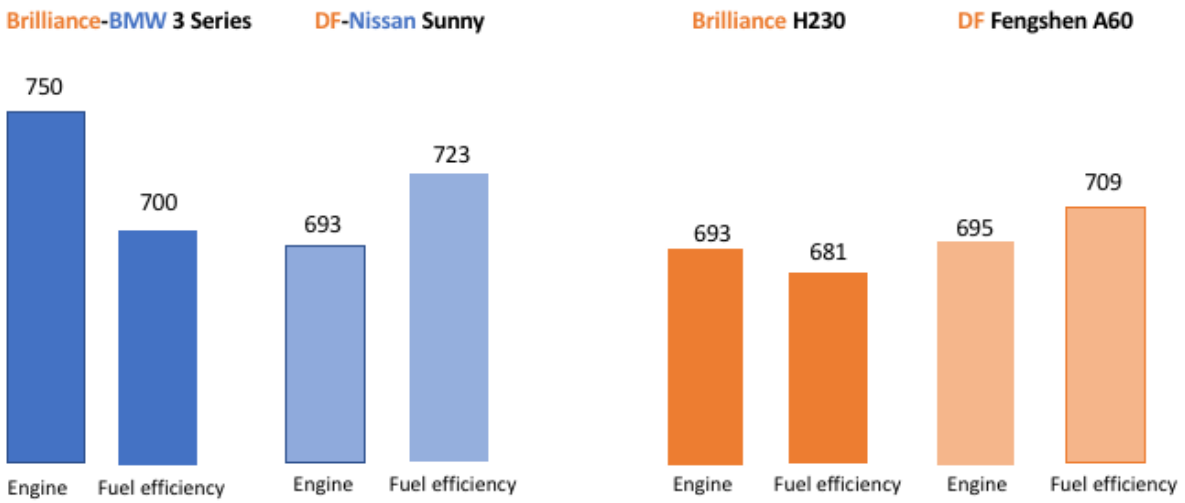
Notes: This figures shows a map of vehicle production cities in China. Each circle represents a city. Colors of the circle indicate the ownership composition of the production plants located in a given city.

Figure 5: Descriptive Patterns of Quality Upgrading



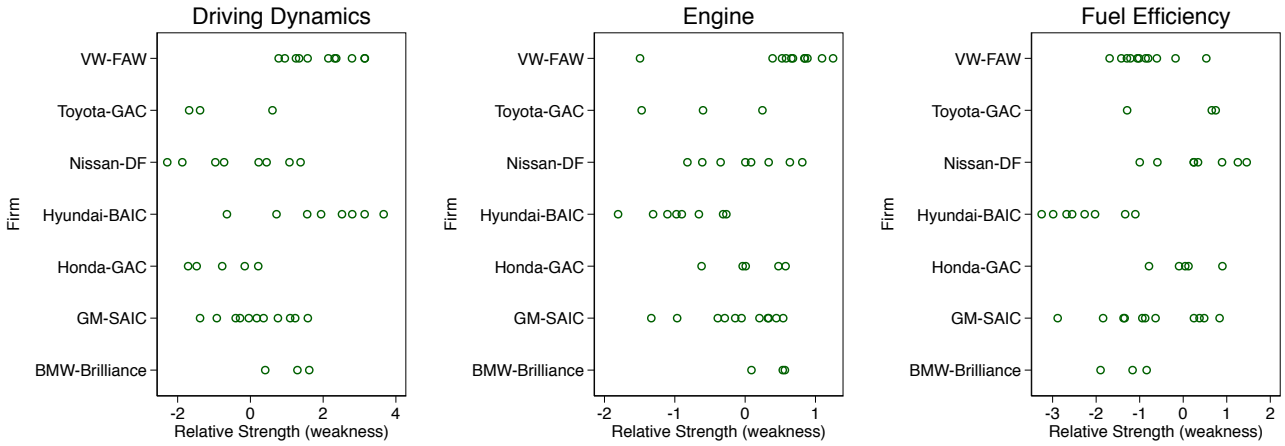
Notes: The IQS scores report the number of problems experienced per 100 vehicles during the first 90 days of ownership across nine performance dimensions. The aggregate score (left figure) is the sum of the nine subscores. The middle and right figures show the time dynamics of two subscores, namely engine and transmission and features/control/display. The IQS scores are multiplied by negative 1 so that a larger value indicates higher quality (i.e., fewer number of defects).

Figure 6: Leader-Follower Pattern of Relative Quality Strength



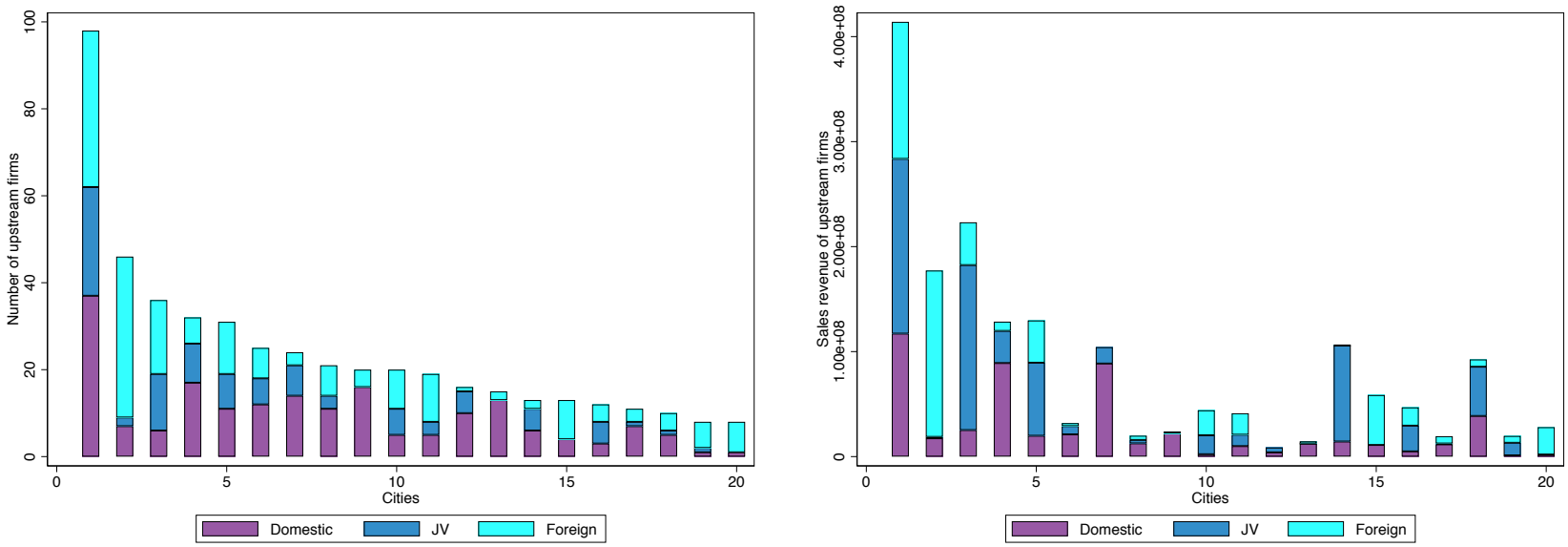
Notes: The bars show the quality scores for engine and fuel efficiency dimensions. The two models on the left are produced by JVs and those on the right are indigenous brands produced by affiliated domestic automakers.

Figure 7: Differential Relative Quality Strength Among Leaders



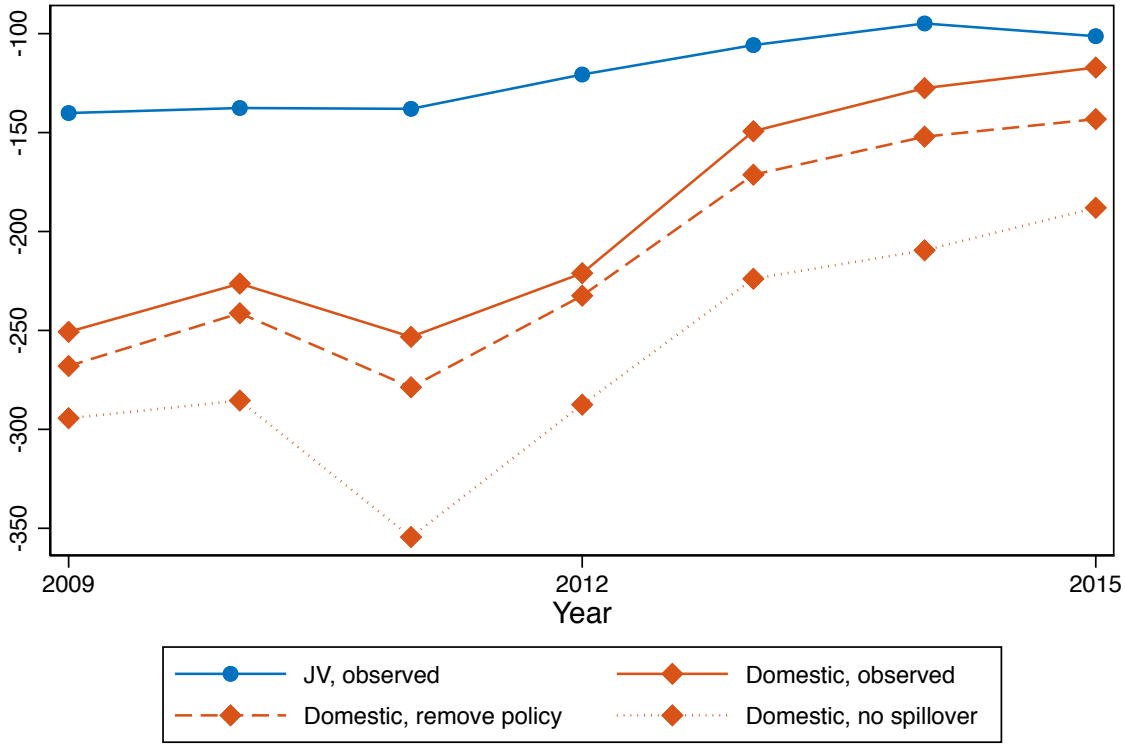
Notes: This figure shows relative quality strength (after partialling out model and subscore-segment fixed effects) across JVs along three vehicle performance dimensions measured in APEAL, namely driving dynamics, engine and fuel efficiency. Each circle represents a model produced by a given firm. The sample includes vehicle models in all segments in 2014.

Figure 8: 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.

Figure 9: Counterfactual Quality Upgrading



Notes: The solid lines plot the observed average quality improvements 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 the *quid pro quo* policy was lifted in 2009. The dotted line shows the counterfactual quality dynamics if spillovers via both ownership affiliation and geographical proximity were shut down.

Table 1: Joint Ventures in the Chinese Passenger Vehicle Market

Joint Venture	Foreign Partner	Chinese Partner	2015 Sales	2015 Market share
VW-FAW	Volkswagen	First Auto Works	1722	.104
GM-Shanghai	General Motors	Shanghai Auto	1634	.099
VW-Shanghai	Volkswagen	Shanghai Auto	1570	.095
Hyundai-Beijing	Hyundai	Beijing Auto	1010	.061
Nissan-Dongfeng	Nissan	Dongfeng Motors	983	.06
Ford-Changan	Ford	Changan Auto	966	.058
Citroen-Dongfeng	PSA	Dongfeng Motors	669	.04
Toyota-FAW	Toyota	First Auto Works	625	.038
Kia-Yueda-Dongfeng	Kia Motors	Dongfeng Motors	587	.036
Honda-Guangzhou	Honda	Guangzhou Auto	563	.034
GM-Shanghai-Wuling	General Motors	Shanghai Auto	436	.026
Toyota-Guangzhou	Toyota	Guangzhou Auto	421	.025
Honda-Dongfeng	Honda	Dongfeng Motors	366	.022
BMW-Brilliance	BMW	Brilliance Auto	283	.017
Mercedes-Beijing	Daimler	Beijing Auto	227	.014
Suzuki-Changan	Suzuki	Changan Auto	88	.005
Mazda-FAW	Mazda	First Auto Works	77	.005
Suzuki-Changhe	Suzuki	Changhe Auto	67	.004
JMC	Ford, Isuzu	Jiangling Motors	55	.003
Mitsubishi-Southeast	Mitsubishi	Southeast Auto	53	.003
Mitsubishi-Guangzhou	Mitsubishi	Guangzhou Auto	51	.003
Fiat-Guangzhou	Fiat	Guangzhou Auto	33	.002
Citroen-Changan	PSA	Changan Auto	26	.002
Infiniti-Dongfeng	Nissan	Dongfeng Motors	15	.001
Landrover-Chery	Jaguar Land Rover	Chery	14	.001
Qoros	Israel Corporation	Chery	12	.001
Total			12553	0.76

Notes: This table shows the sales and market shares of JVs in 2015. Sales are denoted in thousand.

Table 2: Summary Statistics: IQS and APEAL Scores

Ownership	JV				Affiliated Domestic Firms				Non-Affiliated Domestic Firms			
Year	2009		2014/5		2009		2014/5		2009		2014/5	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Panel A: IQS scores (2009-2015)												
IQS 1: Audio/entertainment/navigation	-5.44	3.67	-6.83	3.74	-8.8	8.4	-7.75	5.55	-6.62	3.48	-7.56	5.47
IQS 2: The driving experience	-29.39	14.35	-10.57	5.67	-35.64	18.5	-15.02	10	-50.63	13.41	-11.84	5.7
IQS 3: Engine	-22.63	10.25	-14.17	5.72	-34.48	19.55	-18.15	6.91	-44.14	9.32	-17.44	6.37
IQS 4: Features/controls/displays	-13.53	7.87	-9.23	3.87	-30.51	9.06	-9.63	3.81	-28.57	9.71	-10.95	5.8
IQS 5: HVAC problems	-16.39	7.23	-6.74	4.15	-25.41	10.46	-7.76	4.76	-27.32	8.34	-8.1	5.17
IQS 6: Interior problems	-13.39	6.52	-23.54	8.26	-17.06	8.49	-27.35	10.81	-22.41	8.58	-23.1	7.33
IQS 7: Seat problems	-5.21	3.67	-8.29	4.55	-5.42	4.46	-9.31	4.79	-7.85	3.43	-8.46	4.1
IQS 8: Transmission	-13.61	9.91	-2.72	2.42	-20.87	11.39	-3.66	3.25	-33.88	10.79	-3.88	3.35
IQS 9: Exterior problems	-23.19	13.72	-19.4	8.28	-38.06	18.65	-25.72	10.38	-47.74	17.11	-19.67	8.42
IQS *total*	-142.79	55.65	-101.49	25.34	-216.25	86.64	-124.34	35.09	-269.15	43.89	-110.99	17.63
Panel B: APEAL scores (2009-2014)												
APEAL 1: Audio, entertainment, and navigation	93.65	22.89	96.64	20.9	87.58	25.74	91.66	14.94	70.11	10.49	92.2	16.42
APEAL 2: Engine and transmission	40.68	1.92	40.21	1.32	38.58	2.99	38.63	.82	36.41	1.23	38.37	.79
APEAL 3: Exterior	58.99	2.49	57.51	1.88	57.23	4.56	55.66	1.19	55.14	1.76	55.24	.91
APEAL 4: Heating, ventilation, and air conditioning	65.78	3.12	64.5	2.14	62.15	5.72	62.37	1.32	60.4	1.99	61.94	1.04
APEAL 5: Visibility and driving safety	71.8	5.96	72.12	3.89	68.14	8.35	69.52	3.34	63.3	5.14	69.24	3.2
APEAL 6: Driving dynamics	65.79	2.94	64.43	2.16	62.64	5.27	62.27	1.5	59.77	2.25	61.75	1.25
APEAL 7: Fuel economy	15.96	.63	15.86	.45	15.56	.7	15.44	.3	14.82	.45	15.32	.32
APEAL 8: Interior	114.12	5.64	112.4	3.56	109.87	8.8	108.79	2.12	105.4	3.01	108.24	1.77
APEAL 9: Seats	114.47	9.1	113.34	5.58	111.2	11.7	110.06	4.38	105.83	7.47	108.42	1.91
APEAL 10: Storage and space	89.39	5.94	87.59	4.71	86.53	8.18	83.4	4.51	80.74	6.33	82.15	4.65
APEAL *average*	73.06	5.21	72.46	3.97	69.95	7.58	69.78	2.23	65.19	2.96	69.29	2.47
Num of firms	22		28		12		13		14		12	
Num of models	66		135		22		59		47		61	

Notes: The scores are at the model-by-year level, averaged over responses by around 100 car owners for each model-year. IQS subscores measure the number of problem per 100 vehicle in the first three months of ownership in nine specific subscore categories. APEAL subscores measure owners' emotional attachment and level of excitement in ten vehicle performance categories. The survey design changed significantly for APEAL in 2015, so we report the APEAL subscores in 2014. Non-affiliated domestic firms include all private Chinese automakers and independent SOEs that are not part of any JV.

Table 3: Summary Statistics of the Supplier Network

	Mean	Std. Dev.	Min	P1	P5	P25	P50	P75	P95	P99	Max
Panel A: by suppliers											
Number of model-parts	18.1	43.8	1	1	1	2	7	17	68	185	783
Number of models	11.1	20.6	1	1	1	2	5	12	40	113	259
Number of parts	2.8	4.0	1	1	1	1	1	3	9	20	52
Number of categories covered	1.9	1.8	1	1	1	1	1	2	5	10	18
Observations	1378										
Panel B: by vehicle parts											
Number of supplier-models	92.3	137.8	1	1	3	24	52	110	334	599	1437
Number of models	65.4	68.6	1	1	3	22	44	83	202	331	397
Number of suppliers	14.3	15.0	1	1	1	5	11	18	39	91	104
Observations	271										
Panel C: by model											
Number of supplier-parts	54.5	53.1	1	1	2	16	40	73	162	244	353
Number of suppliers	33.5	29.3	1	1	2	12	26	46	95	142	166
Number of parts	38.6	32.7	1	1	2	14	30	55	107	138	152
Number of categories with suppliers	16.0	8.7	1	1	1	9	16	24	29	31	31
Observations	459										

Notes: The supplier network data is collected by Marklines through its Who Supplies Whom project. The sample consists of 25,004 observations at the supplier-model-part level. An observation shows that a given supplier has supplied the given part for the given model since 2008. There are 2543 distinct part suppliers in the original data. We group suppliers that are subsidiaries of the same parent firm, and this reduces the number of distinct suppliers to 1,378. The data covers 271 distinct vehicle parts under 31 part categories.

Table 4: Relative Quality Strength among JVs

Dep. var: FollowerScore	(1)	(2)
LeaderScore	-0.020***	-0.018***
	(0.001)	(0.002)
LeaderScoreXSameFirm	0.177***	0.122***
	(0.021)	(0.023)
Observations	569962	529777
Partialing out:		
ScoreYear FE	✓	✓
ModelYear FE	✓	
ScoreSegment FE	✓	
ModelScore FE		✓

Notes: The dependent variable is the quality score of a follower model. We consider all pairs of models produced by JVs. For each pair, we randomly assign one as the leader and one as the follower. The unit of observation is a pair-year-subscore. Both leader and follower scores are residualized scores after taking out score-year, model-year and score-segment fixed effects in Column (1), and score-year and model-score fixed effects in Column (2). Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 5: Knowledge Spillover from JVs to Domestic Firms

	(1)	(2)
JVScore	-0.002	-0.002
	(0.002)	(0.002)
JVScoreXSameGroup	0.029**	0.004
	(0.015)	(0.014)
JVScoreXSameSeg		0.002
		(0.002)
JVScoreXSameSegSameGroup		0.145***
		(0.021)
Observations	585523	585523
Partialing out:		
ModelYear FE	✓	✓
ScoreYear FE	✓	✓
ScoreSegment 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-subscore. Both leader (JV) and follower (domestic) scores are residualized scores after taking out score-year, model-year and score-segment fixed effects. SameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group. SameSeg is an indicator variable that equals to 1 if the two models belong to the same vehicle segment. SameSegSameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group and the same vehicle segment. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 6: Knowledge Spillover: Heterogeneity by Founding Year of JV

	(1)	(2)	(3)
Founding Year	Before 2000	2000-2004	2005-2009
JVScore	-0.002	-0.002	-0.000
	(0.004)	(0.002)	(0.011)
JVScoreXSameGroup	-0.003	0.005	0.214
	(0.021)	(0.010)	(0.135)
JVScoreXSameSeg	-0.004	0.008	-0.007
	(0.006)	(0.006)	(0.008)
JVScoreXSameSegSameGroup	0.210***	0.062**	-0.605
	(0.031)	(0.030)	(0.398)
Observations	305976	255341	9139
Partialing out:			
ModelYear FE	✓	✓	✓
ScoreYear FE	✓	✓	✓
ScoreSegment 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) restrict to models produced by JVs that are formed prior to 2000. Column (2) restrict to models produced by JVs that are formed between 2000 and 2004. Column (3) restrict to models produced by JVs that are formed after 2004. The unit of observation is a pair-year-subscore. Both leader (JV) and follower (domestic) scores are residualized scores after taking out score-year, model-year and score-segment fixed effects. SameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group. SameSeg is an indicator variable that equals to 1 if the two models belong to the same vehicle segment. SameSegSameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group and the same vehicle segment. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 7: Knowledge Spillover: Exploring Temporal Variation

	(1)	(2)
JVScore	-0.003***	-0.004**
	(0.001)	(0.002)
JVScoreXSameGroup	0.052***	0.029**
	(0.013)	(0.014)
JVScoreXSameSeg		0.007
		(0.008)
JVScoreXSameSegSameGroup		0.122***
		(0.026)
Observations	515090	515090
Partialing out:		
ModelScore FE	✓	✓
ScoreYear 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-subscore. Both leader (JV) and follower (domestic) scores are residualized scores after taking out score-year and model-score fixed effects. SameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group. SameSeg is an indicator variable that equals to 1 if the two models belong to the same vehicle segment. SameSegSameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group and the same vehicle segment. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 8: Alternative Explanation: Overlapping Customer Base

Dep. variable: log(count of top two choices + 1)	(1)	(2)	(3)
SameGroup	-0.0284***	0.00738***	-0.00187
	(0.00225)	(0.00226)	(0.00227)
SameSegment		0.0668***	0.0444***
		(0.00206)	(0.00213)
SameOwnershipType		0.0445***	0.0378***
		(0.00144)	(0.00144)
SameOwnershipTypeSameSegment		0.147***	0.143***
		(0.00310)	(0.00308)
SameFirm		0.0352***	0.0258***
		(0.00332)	(0.00332)
Constant	0.0707***	0.0205***	0.0705***
	(0.000662)	(0.000962)	(0.00154)
Observations	196225	196225	196225
R-squared	0.0152	0.0812	0.0925
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, engine displacement, and number of safety and comfort features. 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 JV-SOE.

Table 9: Knowledge Spillover by IQS and APEAL Studies

	(1) All	(2) IQS	(3) APEAL
JVScore	-0.002	-0.001	-0.003
	(0.002)	(0.001)	(0.004)
JVScoreXSameGroup	0.004	0.001	0.007
	(0.014)	(0.010)	(0.026)
JVScoreXSameSeg	0.002	-0.001	0.005**
	(0.002)	(0.003)	(0.002)
JVScoreXSameSegSameGroup	0.145***	0.138***	0.151***
	(0.021)	(0.029)	(0.029)
Observations	585523	277353	308170
Partialing out:			
ModelScore FE	✓	✓	✓
ScoreYear FE	✓	✓	✓
ScoreSegment FE	✓	✓	✓

Notes: Column (1) replicates Column (2) of Table 5. Column (2) and (3) split IQS and APEAL subscores into different regression samples. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 10: Alternative Explanation: Learning by Doing

	(1)	(2)	(3)
Sample: pairs in the ...	Same Segment	Same Segment + Same Group	Same Segment + Different Group
JVScore	0.000	-0.055	0.056
	(0.003)	(0.408)	(0.045)
JVScoreXSameGroup	0.149***		
	(0.025)		
JVScoreXLnJVSales		-0.046**	-0.004
		(0.022)	(0.005)
JVScoreXLnDomSales		0.064**	0.001
		(0.031)	(0.008)
Observations	114722	3363	54777
Partialing out:			
ModelScore FE	✓	✓	✓
ScoreYear FE	✓	✓	✓
ScoreSegment FE	✓	✓	✓

Notes: Column (1) considers pairs of JV-domestic models in the same vehicle segment. Column (2) restrict to pairs in the same segment and same JV group. Column (3) considers those in the same segment but different groups (including models produced by non-affiliated firms). Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 11: Knowledge Spillover: the Role of Geography

	(1) Sample: Same-segment pairs	(2) Sample: All pairs
JVScoreXSameSegSameGroupSameCity	0.200***	0.200***
	(0.038)	(0.038)
JVScoreXSameSegSameGroupDiffCity	0.104***	0.104***
	(0.023)	(0.023)
JVScoreXSameSegDiffGroupSameCity	0.144*	0.144*
	(0.084)	(0.084)
JVScoreXSameSegDiffGroupDiffCity	-0.001	-0.001
	(0.005)	(0.005)
JVScoreXDiffSegSameGroupSameCity		0.066***
		(0.025)
JVScoreXDiffSegSameGroupDiffCity		-0.028
		(0.021)
JVScoreXDiffSegDiffGroupSameCity		0.110***
		(0.032)
JVScoreXDiffSegDiffGroupDiffCity		-0.003
		(0.004)
Observations	114722	585523
Partialing out:		
ModelYear FE	✓	✓
ScoreYear FE	✓	✓
ScoreSegment FE	✓	✓

Notes: The dependent variable is the quality score of a domestic model. Column (1) considers pairs of JV-domestic models in the same vehicle segment. Column (2) considers all JV-domestic pairs. The unit of observation is a pair-year-subscore. Both leader (JV) and follower (domestic) scores are residualized scores after taking out score-year, model-year and score-segment fixed effects. Interaction terms are dummy variables indicating whether the two models are in the same vehicle segment, same JV group, and same city. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 12: Determinants of Supplier Overlap

Dep var: number of shared suppliers	(1)	(2)
Same Group	0.966***	
	(0.125)	
Same City		2.12***
		(0.227)
Constant	3.185	3.238
	(0.0457)	(0.0433)
Observations	8601	8601

Note: The dependent variable is the number of common suppliers shared by a given pair of JV-domestic models. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 13: Mechanism of Knowledge Spillover: Supplier Network

	(1)	(2)
Panel A. Ownership Affiliation		
JVScoreXSameGroup	0.144***	0.097***
	(0.022)	(0.024)
JVScoreXDiffGroup	-0.000	-0.001
	(0.002)	(0.002)
JVScoreXSameGroupXSupplierOverlapRatio		0.043***
		(0.015)
JVScoreXDiffGroupXSupplierOverlapRatio		0.013***
		(0.001)
Observations	111796	111796
Panel B. Geographical Proximity		
JVScoreXSameCity	0.185***	0.116***
	(0.032)	(0.033)
JVScoreXDiffCity	0.002	0.000
	(0.002)	(0.002)
JVScoreXSameCityXSupplierOverlapRatio		0.087***
		(0.026)
JVScoreXDiffCityXSupplierOverlapRatio		0.015***
		(0.001)
Observations	111359	111359

Notes: The sample consists of JV-domestic pairs in the same vehicle segment. The unit of observation is a pair-year-subscore. Both JV and domestic scores are residualized scores after taking out score-year, model-year and score-segment fixed effects. Supplier overlap ratio 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-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table 14: Mechanism of Knowledge Spillover: Labor Mobility

Panel A: All Workers

	New Job							
Old Job	JV		Independent		Affiliated		Total	
	No.	%	No.	%	No.	%	No.	%
JV	152	40.5	132	35.2	91	24.3	375	100.0
Independent	148	27.6	215	40.0	174	32.4	537	100.0
Affiliated	237	32.9	279	38.8	204	28.3	720	100.0
Total							1,632	

.

Panel B: Skilled Workers

	New Job							
Old Job	JV		Independent		Affiliated		Total	
	No.	%	No.	%	No.	%	No.	%
JV	64	36.6	74	42.3	37	21.1	175	100.0
Independent	94	25.9	147	40.5	122	33.6	363	100.0
Affiliated	120	30.6	175	44.6	97	24.7	392	100.0
Total							930	

Note: The data are based on the work history from LinkedIn (China) users who have worked in one of the automakers in our analysis. This table only focuses on the workers who have changed employer at least once based on the online profile. Skilled workers are defined as those whose positions are in areas of engineering, design, IT, procurement and research.

Table 15: 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)
JVScoreXSameCityXCitywithAffiliatedSOE	0.087**
	(0.044)
JVScoreXSameCityXCitywithoutAffiliatedSOE	0.214***
	(0.040)
Observations	552235
Partialing out:	
ModelYear FE	✓
ScoreYear FE	✓
ScoreSegment 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-subscore. Both leader (JV) and follower (domestic) scores are residualized scores after taking out model-year, score-year and score-segment fixed effects. SameCity is an indicator variable that equals to 1 if the two models are produced in the same city. CitywithAffiliatedSOE and CitywithoutAffiliatedSOE are dummy variables indicating whether the city hosts an auto assembly plant by the affiliated SOEs. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

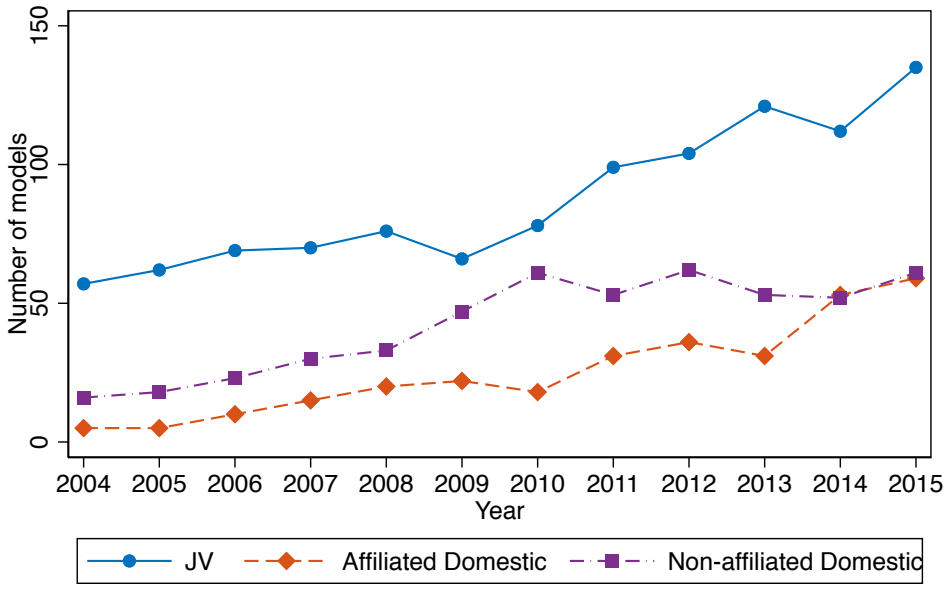
Table 16: Knowledge Spillover: Evidence from the Upstream Auto Parts Industry

	Simple average quality				Weighted average quality			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average JV Quality	0.696***	-0.050*	-0.094***	0.368***				
	(0.035)	(0.029)	(0.031)	(0.062)				
Average Foreign Quality	0.599***	0.189***	0.211***	0.437***				
	(0.029)	(0.021)	(0.021)	(0.038)				
Average JV Quality (weighted)					0.689***	0.017	-0.008	0.085***
					(0.038)	(0.028)	(0.027)	(0.031)
Average Foreign Quality (weighted)					0.570***	0.163***	0.179***	0.242***
					(0.031)	(0.021)	(0.020)	(0.026)
Observations	3538	3538	3538	3531	3612	3612	3612	3606
Year FE		✓	✓	✓		✓	✓	✓
PartCateg FE		✓	✓			✓	✓	
City FE			✓				✓	
City-PartCateg FE				✓				✓

Notes: The dependent variable is the quality of a domestic part suppliers. The unit of observation is a supplier-part category-year. The key regressors are the average quality of JVs and wholly owned foreign suppliers in the same city for a given part category in a given year. Standard errors are clustered at the city level. Column (1) to (4) compute simple average quality among the JV and foreign firms. Column (5) to (8) compute sales-weighted average quality of the leaders in a given city-part category-year. *** implies significance at 0.01 level, ** 0.5, * 0.1.

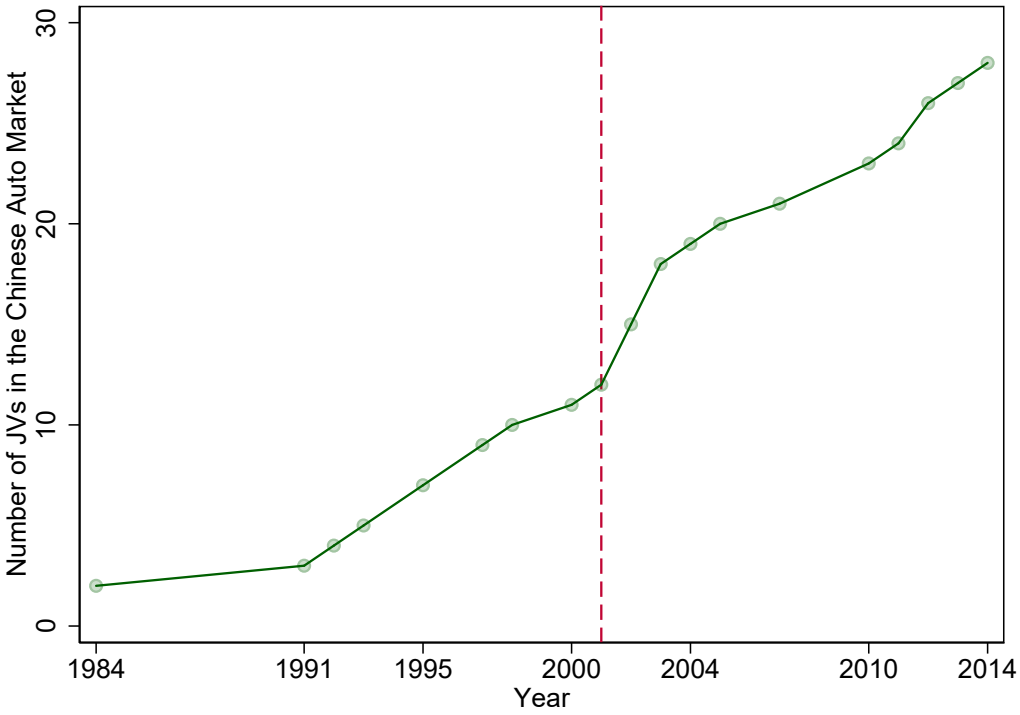
Appendix Tables and Figures

Figure A.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 A.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.

Table A.1: List of Top Models by Sales in 2015

Rank	Model Name	Firm	2015 Sales	2015 Mkt. share
Joint Venture Models				
1	Buick-Shanghai Excelle	GM-SAIC	468	.028
2	VW-Shanghai Lavida	VW-SAIC	355	.021
3	Nissan-DF ZNA Bluebird Sylphy	Nissan-DF	348	.021
4	Hyundai-Beijing Elantra	Hyundai-BAIC	329	.02
5	Toyota-FAW Corolla EX	Toyota-FAW	313	.019
6	Baojun 730	SAIC-GM-Wuling	295	.018
7	VW-FAW Sagitar	VW-FAW	281	.017
8	VW-FAW Jetta	VW-FAW	267	.016
9	VW-Shanghai Polo	VW-SAIC	259	.016
10	Ford-Changan Focus	Ford-Chana	252	.015
Domestic Models				
1	Great Wall Haval H6	Great Wall	368	.022
2	Emgrand EC7-Series	Geely	191	.012
3	Chana Eado	Chana	184	.011
4	Chery Tiggo	Chery	159	.01
5	Chana CS75	Chana	154	.009
6	Great Wall Haval H2	Great Wall	152	.009
7	Chana CS35	Chana	147	.009
8	Chana Yuexiang	Chana	132	.008
9	JAC Refine (Ruifeng) S3	JAC	114	.007
10	Guangzhou Auto Trumpchi GS4	GAC	101	.006

Notes: sales are quoted in thousands.

Table A.2: 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 subscores. We first standardize all the survey responses within a given subscore by stacking all model-year observations together and compute the z-score for each question. The standardized z-scores are then aggregated to the subscore level.

Table A.3: 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 A.4: Knowledge Spillover: Alternative Clustering of Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)
Clustering:	DomesticFirm-Score JVFirm-Score		Domestic-JVFirmPair-Score		Domestic-JVFirmPair-Score DomesticFirm-Score-Year, JVFirm-Score-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)
JVScoreXSameGroup	0.029**	0.004	0.029*	0.004	0.029***	0.004
	(0.015)	(0.014)	(0.015)	(0.014)	(0.011)	(0.011)
JVScoreXSameSeg		0.002		0.002		0.002
		(0.002)		(0.006)		(0.003)
JVScoreXSameSegSameGroup		0.145***		0.145***		0.145***
		(0.021)		(0.025)		(0.020)
Observations	585523	585523	585523	585523	585523	585523
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)
JVScoreXSameGroup	0.029	0.004	0.029	0.004	0.029	0.004
	(0.036)	(0.036)	(0.066)	(0.060)	(0.061)	(0.056)
JVScoreXSameSeg		0.002		0.002		0.002
		(0.003)		(0.016)		(0.008)
JVScoreXSameSegSameGroup		0.145***		0.145**		0.145***
		(0.048)		(0.067)		(0.052)
Observations	585523	585523	585523	585523	585523	585523
Partialing out:						
ModelYear FE	✓	✓	✓	✓	✓	✓
ScoreYear FE	✓	✓	✓	✓	✓	✓
ScoreSegment FE	✓	✓	✓	✓	✓	✓

Note: This table replicates the specifications in Table 5 under alternative clustering of the standard errors.

Table A.5: Knowledge Spillovers: Which Models of JVs to Learn From?

Sample: pairs in the same segment	(1)	(2)	(3)
JVScore	0.000	0.001	-0.006
	(0.003)	(0.008)	(0.004)
JVScoreXSameGroup	0.149***	0.134***	0.155***
	(0.025)	(0.029)	(0.027)
JVScoreXJVFlagship		-0.002	
		(0.017)	
JVScoreXSameGroupXJVFlagship		0.037	
		(0.054)	
JVScoreXJVBestModel			0.032***
			(0.011)
JVScoreXSameGroupXJVBestModel			-0.029
			(0.053)
Observations	114722	114722	114722
Partialing out:			
ModelYear FE	✓	✓	✓
ScoreYear FE	✓	✓	✓
ScoreSegment FE	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We consider pairs of models produced by JVs and domestic firms that are in the same vehicle segment. The unit of observation is a pair-year-subscore. Both leader (JV) and follower (domestic) scores are residualized scores after taking out score-year, model-year and score-segment fixed effects. SameGroup is an indicator variable that equals to 1 if the two models belong to the same JV group. JVFlagship is a dummy variable indicating the top three best-selling JV models in the same segment based on aggregate sales during the sample period. JVBestModel is a dummy variable indicating the model with the highest quality in a given segment produced by the JV firm. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table A.6: Knowledge Spillovers: Fixed Effects Models

	(1)	(2)	(3)
JVScore	-0.002	-0.003	-0.004*
	(0.001)	(0.002)	(0.002)
JVScoreXSameGroup	0.019	0.019	0.029
	(0.016)	(0.017)	(0.028)
JVScoreXSameSeg	0.003**	0.003*	0.006
	(0.001)	(0.002)	(0.004)
JVScoreXSameSegSameGroup	0.099***	0.100***	0.163***
	(0.019)	(0.019)	(0.026)
Observations	585523	585523	585523
Fixed Effects:			
ScoreYear FE	✓	✓	✓
DomesticModel-Year FE	✓	✓	
Score-DomesticSegment FE	✓	✓	
JVModel-Year FE		✓	
Score-JVSegment FE		✓	
Pair-Year FE			✓
Score-PairSegment FE			✓

Notes: This table replicates the specification in Column (2) of Table 5. Instead of residualized scores, the JV and domestic scores are standardized IQS and APEAL subscores without taking out fixed effects. Column (1) to (3) control for different combinations of fixed effects at the leader, follower and pair level. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table A.7: Knowledge Spillovers: Sales Weighted Regressions

	(1)	(2)	(3)	(4)
	Leader's cumulative sales till current year		Leader's current-year sales	
JVScore	-0.004**	-0.003	-0.005	-0.006**
	(0.002)	(0.002)	(0.004)	(0.003)
JVScoreXSameGroup	0.065***	0.039***	0.093***	0.056***
	(0.013)	(0.010)	(0.023)	(0.016)
JVScoreXSameSeg		-0.005		0.001
		(0.006)		(0.005)
JVScoreXSameSegSameGroup		0.124***		0.175***
		(0.031)		(0.035)
Observations	1.10e+11	1.10e+11	4.26e+10	4.26e+10
Partialing out:				
ModelYear FE	✓	✓	✓	✓
ScoreYear FE	✓	✓	✓	✓
ScoreSegment FE	✓	✓	✓	✓

Notes: This table replicates the specification in Table 5, weighted by sales of the JV model. Standard errors are clustered at FollowerFirm-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.

Table A.8: Knowledge Spillover: Lagged Leader's Score

	(1)	(2)	(3)	(4)
JVScoreXL0Year	-0.002**			
	(0.001)			
JVScoreXSameGroupXL0Year	0.004			
	(0.014)			
JVScoreXSameSegXL0Year	0.002			
	(0.002)			
JVScoreXSameSegSameGroupXL0Year	0.145***			
	(0.021)			
JVScoreXL1Year		0.002***		
		(0.000)		
JVScoreXSameGroupXL1Year		-0.014		
		(0.009)		
JVScoreXSameSegXL1Year		-0.008**		
		(0.003)		
JVScoreXSameSegSameGroupXL1Year		0.054*		
		(0.029)		
JVScoreXL2Year			0.002***	
			(0.000)	
JVScoreXSameGroupXL2Year			-0.018***	
			(0.006)	
JVScoreXSameSegXL2Year			-0.007	
			(0.004)	
JVScoreXSameSegSameGroupXL2Year			0.033	
			(0.022)	
JVScoreXL3Year				0.000
				(0.000)
JVScoreXSameGroupXL3Year				-0.012
				(0.009)
JVScoreXSameSegXL3Year				0.001
				(0.004)
JVScoreXSameSegSameGroupXL3Year				0.010
				(0.019)
$_cons$	-0.000	-0.000	-0.000	-0.000
	(0.096)	(0.088)	(0.084)	(0.084)
Observations	585523	488357	383154	284886
Partialing out:				
ModelYear FE	✓	✓	✓	✓
ScoreYear FE	✓	✓	✓	✓
ScoreSegment FE	✓	✓	✓	✓

Notes: This table replicates the specification in Column (2) of Table 5 using leaders' quality measures in the past. 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-Score and LeaderFirm-Score level. *** implies significance at 0.01 level, ** 0.5, * 0.1.