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

Jie Bai Panle Jia Barwick Shengmao Cao Shanjun Li*

June 27, 2024

Abstract

This paper studies the impact of FDI via *quid pro quo* (technology for market access) in facilitating knowledge spillovers and quality upgrading. Our context is the Chinese automobile industry, where foreign automakers are required to set up joint ventures (JVs) with domestic automakers to facilitate technology transfers in return for market access. Our identification strategy exploits a unique dataset of detailed vehicle quality measures and relies on *within*-product variation across quality dimensions. We show that affiliated domestic automakers tend to adopt the quality strengths of their JV partners, consistent with knowledge spillovers. We rule out alternative explanations, such as endogenous JV formation, geographic proximity, overlapping customer bases, brand image association, and patent transfers. Additional analysis suggests that worker flows and supplier networks mediate knowledge spillovers. Overall, knowledge spillovers due to ownership affiliation under *quid pro quo* contributed 8.3% of the quality improvement experienced by affiliated domestic models between 2001 and 2014, relative to nonaffiliated domestic models.

Keywords: FDI, joint venture, knowledge spillovers, quality upgrading

JEL classification: F23, O14, O25

---

*Contact: Bai: Harvard Kennedy School and NBER (email: jie_bai@hks.harvard.edu); Barwick: Department of Economics, University of Wisconsin-Madison and NBER (email: pbarwick@wisc.edu); Cao: Department of Strategy, Kellogg School of Management (email: shengmao.cao@kellogg.northwestern.edu); Li: Dyson School of Applied Economics and Management, Cornell University and NBER (email: sl2448@cornell.edu). We thank David Atkin, Lauren Bergquist, Loren Brandt, Meghan Busse, Davin Chor, Kerem Cosa, Dave Donaldson, Jeffery Frankel, Asim Khwaja, Gabriel Kreindler, Gordon Hanson, James Harrigan, Hanwei Huang, Wolfgang Keller, Robert Lawrence, Ernest Liu, Benjamin Olken, Jessica Pan, Ivan Png, Yu Qin, Dani Rodrik, Meredith Startz, Heiwai Tang, Eric Verhoogen, Shaoda Wang, Shangjin Wei, Tom Wollmann, Daniel Xu, and seminar and conference participants at Baruch College, the Beijing International Trade and Investment Symposium, Bank of Canada–Tsinghua PBCSF–University of Toronto Conference on the Chinese Economy, China Economics Summer Institute, Columbia University, Georgetown University, George Washington University, Harvard Kennedy School, IGC-Stanford conference on firms, trade and development, Johns Hopkins University, Microsoft Economics, MIT, National University of Singapore, NBER Chinese Economy Workshop, NBER Industrial Organization Workshop, NBER Development/BREAD (preconference), Stanford, trade seminar at Hong Kong Universities, University of Alberta, University of Toronto, University of Virginia, University of Zurich, UPenn China Seminar, US Census Bureau, World Bank Development Research Group, and Yale for helpful comments. We thank Qinghua Wang, Ann Xie, Minghuang Zhang, and Shana Zhuang for generous data support, and Luming Chen, Yikuan Ji, Youming Liu, Yiding Ma, Binglin Wang, and Yukun Wang for excellent research assistance. All errors are our own.

1 Introduction

The past several decades have witnessed significant liberalization among developing economies to foreign trade and investment, as advocated by international organizations (UNCTAD, 2018; World Bank, 2018).[1] Nevertheless, for strategic reasons, many emerging economies continue to impose considerable restrictions on foreign direct investment (FDI) in certain sectors. One such policy is *quid pro quo*, which requires multinational firms to transfer technologies to host countries in exchange for market access. This is typically implemented via a joint venture (JV) requirement with a strict cap on the share of foreign equity.[2] While *quid pro quo* via joint ownership more directly exposes firms in developing countries to foreign technology, multinational firms often consider it a form of coerced technology transfer and a significant barrier to investing in developing countries. *Quid pro quo* lies at the forefront of the U.S.–China trade tensions, and concern over this policy was a key stated justification for the Trump administration's decision to impose tariffs on $50 billion worth of Chinese imports in 2018.[3]

Despite the policy relevance of *quid pro quo* and these recent controversies, there is limited empirical evidence on its benefits to the host country. The vast literature on FDI has paid relatively scant attention to whether and how the *form* of FDI matters. In this paper, we attempt to fill this knowledge gap by examining the effectiveness of the JV requirement under *quid pro quo* in facilitating knowledge spillovers from foreign to domestic firms. Unlike previous studies that mostly rely on firm-level total factor productivity (TFP) as the outcome variable, we exploit a rich set of product quality attributes that embody firms' fundamental technological capabilities. These quality measures allow us to look inside the black box of TFP and provide concrete evidence of knowledge spillovers. In addition, a better understanding of industrial quality upgrades is valuable in itself and relevant for both academics and policymakers in developing countries (Verhoogen, 2023).

Our context is the Chinese automobile industry, the largest in the world since 2009. Foreign automakers are mandated to set up JVs with domestic automakers to facilitate technology transfer (the *quid*) in order to produce and sell cars in China (the *quo*). A key stipulation among the set of requirements is a 50% cap imposed on the foreign ownership share. The automobile industry is ideal for studying knowledge spillovers and quality upgrades due to the numerous technological and quality features in final products. Our primary dataset, sourced from J.D. Power, includes rich quality measures across multiple dimensions of vehicle performance that are based on malfunction rates and

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

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

[3] The Office of the U.S. Trade Representative (USTR) issued a report in 2018 on its investigation into China's policies and practices related to technology transfer, intellectual property, and innovation. Forced technology transfer through foreign ownership restrictions is considered a key component of China's technology transfer regime.

driver experience ratings for nearly all car models produced in China from 2001 to 2014. We map these granular quality data onto the entire ownership network to identify knowledge spillovers. To examine the mechanisms of knowledge flow and explore alternative explanations, we leverage additional data on worker flows, parts and components suppliers, patent transfers, auto assembly plant locations, and consumer surveys. To our knowledge, the dataset represents one of the most comprehensive sources of information on China's automobile industry, spanning a period of unprecedented growth from its near-nascence to becoming the world's largest auto market.

We begin by documenting significant quality improvements among Chinese domestic automakers. From 2001 to 2014, malfunction rates of domestically produced car models decreased by over 75%. During this period, the quality gap between domestic models and JV models produced in China also notably narrowed: domestic models had 65% higher malfunction rates than JV models in 2001; by 2014, this gap had reduced to 33%. While many factors contribute to the industry-wide quality upgrades, we focus on the impact of the *quid pro quo* policy. The JVs required by the policy afford affiliated domestic automakers direct exposure to foreign technologies. Therefore, to isolate the knowledge spillovers resulting from ownership affiliation under *quid pro quo*, beyond any industry-wide spillovers from the presence of foreign automakers, we examine whether affiliated domestic automakers ("followers") benefit more in terms of quality upgrades from their foreign partners ("leaders") compared to nonaffiliated domestic automakers.

Our empirical strategy leverages the rich multidimensional quality data and examines whether affiliated domestic followers adopt JV leaders' quality strengths in their independent production. An example helps illustrate the intuition for identification. BMW–Brilliance, a JV between the German automaker BMW and the domestic automaker Brilliance, produces BMW models that have strong engine performance. Toyota–FAW, a JV between the Japanese automaker Toyota and the domestic automaker First Auto Works, produces Toyota models that are fuel efficient. We examine whether Brilliance produces indigenous models with better engine performance and FAW produces more fuel-efficient models relative to indigenous models produced by other domestic automakers.

We implement the empirical strategy in two steps. First, for all JV and domestic models, we construct *within-model relative* quality strength across different dimensions (e.g., engine versus fuel efficiency). Then, we examine the similarity in relative quality strength among models produced by affiliated firms versus models produced by non-affiliated firms. Our main specification controls for the *overall* quality of each model in each period to isolate a model's relative quality strength. This accounts for potential endogenous JV formation whereby foreign and domestic automakers strategically choose each other as partners based on overall quality. In addition, a rich set of fixed effects controls for industry-wide quality differences and quality improvements across vehicle segments (e.g., better safety features in the luxury segment).[4] We find that when a JV model scores one standard deviation higher on a quality dimension, the indigenous models of the affiliated domestic automaker in the same vehicle segment score 0.098 standard deviations higher on the same dimension than the models from other domestic automakers do. The shared relative quality strength between affiliated JV-domestic models is 17% of that among models produced by the same JV firm.

We address a series of alternative explanations. While our main specification accounts for JV formation based on *overall* quality level, one may be concerned about endogenous JV formation based on *relative* strength. For example, domestic automakers may seek foreign partners that are strong on certain quality dimensions to compensate for their own weaknesses or augment their advantages. To address this issue, we first exploit an institutional feature by limiting our sample to JVs formed in the 1980s and 1990s. At that time, China's passenger vehicle market was in its infancy. Most domestic automakers had scant technological know-how in passenger vehicle production. Therefore, it is unlikely that JV partners were matched based on quality strengths. Nevertheless, the pattern of shared quality persists for this sub-sample. We further examine how quality similarity depends on JVs' age, as well as how it evolves over time within an affiliation. The results indicate that quality similarity emerges gradually over time, consistent with the fact that knowledge spillovers could take years to materialize.

Next, we consider the role of geographic proximity. To the extent that production facilities of JVs and their affiliated domestic firms are sometimes located in the same region, the patterns of knowledge spillovers could be partly driven by geographic proximity rather than ownership affiliation per se. Exploring the *partial* overlap between the ownership and geographical networks, we show that while spillovers between affiliated models produced in the same province are the strongest, there remain substantial knowledge spillovers from JVs to affiliated domestic firms located in different provinces.

We also consider potential demand-side confounding factors. One is that affiliated partners might target the same set of consumers and hence design similar products. However, analyses using household vehicle ownership surveys indicate that most car buyers do not consider models from JVs and affiliated domestic partners to be close substitutes. Another potential explanation is brand image association: if consumers perceive affiliated partners as sharing similar quality strength, such perception may then induce domestic firms to strategically specialize in certain quality dimensions to exploit the positive brand image association. To examine this, we conducted two rounds of consumer surveys to measure consumers' awareness of individual JVs. We find imperfect consumer knowledge about ownership affiliation and that stronger JV recognition does not translate into greater similarity in quality strength.

Lastly, we show that the observed patterns of shared quality strength are not driven by explicit market transactions such as patent transfers: a very small number of patent transfers in China's auto

[4] Following the standard classification system, we group models into eight segments: mini sedan, small sedan, compact sedan, medium sedan, large sedan, small-medium sport utility vehicle (SUV), large SUV, and multipurpose vehicle (MPV). Quality is measured in different dimensions, such as the engine, transmission, and interior, as discussed in Section 2.3.

industry originated from a JV. The findings are consistent with Holmes, McGrattan, and Prescott (2015), which shows that JVs file a small number of patent applications in China.

In terms of potential mechanisms, we observe that knowledge spillovers strengthen with cumulative JV production rather than the domestic firms' own past experience. This suggests that knowledge spillovers likely occur through the domestic partner's observation and adoption of JV production processes instead of through domestic firms' internal production. Additional datasets on worker flows and parts suppliers reveal that increased worker mobility facilitates knowledge spillovers to both affiliated and nonaffiliated firms, with a stronger impact on affiliated firms. Higher supplier overlap also predicts stronger spillovers. These findings are consistent with existing literature highlighting the role of worker flows (e.g., Stoyanov and Zubanov (2012); Poole (2013)) and shared suppliers as significant channels for FDI spillovers (e.g., Kee (2015); Alfaro-Urena, Manelici, and Vasquez (2022)).

The baseline estimates suggest that *quid pro quo* improved the quality of domestic affiliated models by 8.3% from 2001 and 2014, in addition to any industry-wide spillovers. Our focus on spillovers via JV affiliation directly addresses the recent policy of lifting the JV requirement while still allowing foreign automakers to operate in China. We conjecture that this policy change would not significantly hinder domestic upgrading going forward, considering that the quality gap between domestic firms and JV firms had significantly narrowed by 2014. The evidence on potential mechanisms, although suggestive, underscores the importance of market-based mechanisms in facilitating knowledge spillovers. Furthermore, foreign firms may have stronger incentives to introduce advanced technologies into China when they have majority stakes and better protection of their know-how (Muller and Schnitzer, 2006; Branstetter and Saggi, 2011). How such incentives may be shaped by global knowledge spillovers remains an important research area (Buera and Oberfield, 2020; Bilir and Morales, 2020).

Our work contributes to several strands of the existing literature. First, it speaks to the extensive empirical literature on FDI spillovers (see Harrison and Rodríguez-Clare 2009 for an excellent review). We highlight three key contributions to this literature. First, we focus on whether and how the *form* of FDI matters, beyond its mere presence. Second, methodologically, we propose a new identification strategy that exploits rich within-product quality measures to control for industry-wide and firm-level potential confounders.[5] Lastly, we look beyond TFP and study the impact on quality upgrading using product-level quality attributes that embed firms' technological capability.[6]

Second, our paper relates to the growing body of work in trade and development that aims to

[5]Existing work has relied mostly on cross-industry variation in the presence or intensity of FDI to identify the impact on the host country (e.g., Haddad and Harrison (1993); Aitken and Harrison (1999); Javorcik (2004); Keller and Yeaple (2009)). However, entry of foreign firms could be driven by unobserved industry-level shocks. Recent studies address this challenge by leveraging external shocks and foreign entry induced by them (e.g., McCaig, Pavcnik, and Wong (2020)).

[6]Most existing studies focus on TFP improvement as the key outcome variable (e.g., Haskel, Pereira, and Slaughter (2007); Keller and Yeaple (2009); Abebe, McMillan, and Serafinelli (2022)), which reflects both the positive spillover effect and the negative competition effect (Kosova, 2010; Lu, Tao, and Zhu, 2017; Fons-Rosen et al., 2017; Jiang et al., 2018).

elucidate the importance of technological innovation and quality upgrades for economic growth (see Verhoogen (2023) for an excellent review). The existing literature focuses mostly on indirect measures of technology and quality improvement, such as market shares and prices (Khandelwal, 2010), as quality is rarely observed in standard firm surveys. Our study adds to a nascent literature leveraging detailed quality measures for specific industries (e.g., Atkin, Khandelwal, and Osman (2017); Macchiavello and Miquel-Florensa (2019); Hansman et al. (2020); Bai et al. (2020); Medina (2022)) to identify knowledge spillovers and examine the impact of FDI on domestic quality upgrades in developing countries.

Third, our study speaks to an emerging literature on the impacts of government-initiated technology transfers (Giorcelli, 2019) and industrial policies (Kalouptsidi, 2017; Wollmann, 2018; Igami and Uetake, 2019; Chen et al., 2021; Lane, 2022; Barwick, Kalouptsidi, and Zahur, 2024) on firm behavior, innovation, and growth. Our analysis allows us to examine the role of China's longstanding *quid pro quo* policy in an important industry. Holmes, McGrattan, and Prescott (2015) quantifies the overall welfare effects of China's *quid pro quo* policy using a multi-country dynamic general equilibrium model, highlighting domestic productivity gains from technology transfer as crucial in determining these welfare effects. Our micro-level approach that leverages detailed industry data to identify spillover impacts on domestic firms complements their macro-level analysis.

2 Background and Data

2.1 Historical Background of *Quid Pro Quo* under Joint Ventures

When China launched its reform and opening-up policy in 1978, the country was an economic and technological backwater. China's automobile manufacturing was low-tech and had limited capacity. Production of passenger vehicles was virtually non-existent.[7] Recognizing the lack of domestic technological know-how, the Chinese government sought FDI to develop manufacturing capabilities. However, there was no established blueprint for partnering with foreign automakers. The concept of forming JVs came to the attention of Chinese policymakers during their meeting with GM's delegation to China in 1978, where foreign automakers offer know-how and product lines as equity while domestic partners provide manufacturing facilities and labor. Appendix A.1 discusses the organizational economics rationale for the JV arrangement as a way of mitigating hold-up risk for foreign firms, incentivizing investment in China, and ultimately facilitating technology transfers to the Chinese market (Eaton and Gersovitz, 1984; Schnitzer, 2002; Muller and Schnitzer, 2006).

The first JV for automobile manufacturing was set up in 1983 between American Motors Corporation (AMC, later acquired by Chrysler Corporation) and Beijing Jeep Corporation Ltd. (now Beijing Automotive Industry Corporation). In 1984, Volkswagen joined with Shanghai Tractor Corporation

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

(now Shanghai Automotive Industry Corporation) to form a second JV in the country. In the early years, foreign automakers used joint ventures as a strategy to avoid the high tariff of around 250% at that time. The majority of manufacturing activities consisted of "knockdown kit" assembly and relied almost exclusively on imported parts. As a result, technology transfer was limited. Appendix A.1 describes the experiences of the early JVs.

To address the early policy deficiencies, *quid pro quo* as a national policy that we know today was formally established in the first-ever industrial policy for the automotive industry in 1994, when China's State Council issued the "Automotive Industry Development Policy." Experiences of early JVs highlighted the need for better technology transfer mechanisms. The 1994 policy addressed this by prohibiting knockdown kits, requiring R&D centers, stipulating the usage of local parts, and capping foreign ownership at 50%. Since the domestic partners of JVs were always state-owned enterprises (SOEs), the Chinese government maintained significant oversight and control over key decisions by JVs. As discussed in Appendix A.1, the 50% cap on foreign ownership in JVs aimed to balance the differing objectives of the Chinese government, domestic automakers, and foreign automakers. It granted Chinese control for facilitating technology transfer to JVs while maintaining foreign investment incentives.

However, because of the strong emphasis on technology transfer, the *quid pro quo* policy has been criticized as a state-sponsored effort to systematically pry technology from foreign companies.[8] Amid recent trade tensions with the U.S., the Chinese government lifted the foreign ownership cap in 2022, representing a major shift away from the *quid pro quo* policy after around four decades. Some have speculated that this policy change could impact not only the Chinese auto industry but also the global industry. Understanding the role played by technology transfer via ownership affiliation is a crucial step toward understanding the implications of this policy shift.

2.2 Growth of the Chinese Auto Industry

Prior to 2000, most affiliated domestic automakers relied on JVs for passenger vehicle production, with few indigenous brands (Figure E.1). In 2004, the central government announced an explicit goal of developing the domestic automotive industry and promoting indigenous brands by supporting R&D activities with tax incentives. The 2009 Automotive Adjustment and Revitalization Plan encouraged mergers, reorganization, and the creation of indigenous brands. Under these government policies, affiliated domestic automakers began launching their own brands. SAIC introduced Roewe in 2006, FAW

[8] Under WTO rules, explicit technology transfer requirements for market access are prohibited. Hence, *quid pro quo* in China has mostly been carried out implicitly via ownership restrictions on JVs to facilitate technology transfer from foreign firms. As part of China's broad industrial policy, it is considered by some countries to create unfair advantages for domestic companies. According to the 2018 China Business Climate Survey Report conducted by the American Chamber of Commerce, 21% of 434 companies surveyed in China faced pressure to transfer technology. Such pressure was most often felt in strategically important industries such as aerospace (44%) and chemicals (41%). Source: http://www.iberchina.org/files/2017/amcham_survey_2017.pdf.

launched Besturn in the same year, and Dongfeng introduced its first model in 2009. By 2014, affiliated domestic automakers had caught up with nonaffiliated domestic automakers in product offerings.

The industry experienced unprecedented growth since 2001, with new passenger vehicle sales increasing from 0.85 million units in 2001 to 24.7 million units in 2017. China surpassed the US in 2009 to become the world's largest car market. In 2017, China alone accounted for over 33% of global auto production and sales. The industry was highly competitive, with 48 firms producing more than 10,000 units each in 2014. The number of JVs also increased steadily (Figure E.2): by 2007, most major automakers had launched JVs in China. Table E.1 lists the JVs and their sales and market shares in 2014. While JVs dominated the industry, domestic firms' sales also grew over time (Figure E.3).[9]

Figure 1 presents a snapshot of the ownership network of the Chinese auto industry in 2014. Many international automakers formed two JVs with different domestic partners. For example, in addition to VW–SAIC, Volkswagen partnered with First Automobile Works Group (FAW) to form VW–FAW in 1991. Likewise, a single domestic firm might have multiple foreign partners. To avoid complications related to intellectual property rights, foreign automakers transfer the production line of a given brand exclusively to one JV. For example, VW–SAIC produces Passat and Tiguan cars, while VW–FAW sells Audi and Jetta brands. There is no product-line overlap between any pair of JVs. All affiliated domestic automakers during our sample period are SOEs. Nonaffiliated domestic automakers (i.e., those without foreign partners) include both SOEs and private firms.

2.3 Data Description

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

Vehicle quality measures Quality measures come from the annual Initial Quality Study (IQS) and Automotive Performance, Execution and Layout Study (APEAL) that were conducted by J.D. Power between 2001 and 2014. Between April and June each year, J.D. Power recruits subjects who purchased a vehicle in the past year in over 50 cities in China and surveys their user experience during the first six months of vehicle ownership. The survey covers major passenger vehicle models in China, which account for over 90% of the market share in terms of sales. The total number of survey respondents for 2014 is 18,884, around 110 car owners per model. The IQS study reports the number of problems experienced per 100 vehicles during the first 90 days of ownership. The survey asks more than 200 questions, covering a complete spectrum of vehicle functionalities, which fall under nine quality dimensions.[10] Industry

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

[10]They are exterior problems, driving experience, feature/control/displays, audio/entertainment/navigation, seat problems, heating/ventilation/air conditioning (HVAC) problems, interior problems, and engine and transmission problems. The IQS includes items such as "Engine doesn't start at all" (engine), "Emergency/parking brake won't hold vehicle" (driving experience), and "Cup holders – broken/ damaged" (interior).

experts believe that initial quality is an excellent predictor of long-term reliability, which has a significant impact on owner satisfaction and brand reputation. The APEAL study elicits user satisfaction ratings over 100 vehicle quality attributes, which are grouped into ten performance dimensions.[11]

Figure E.4 presents the relationship between vehicle prices and the two quality measures. Panel A plots prices against the IQS, with the left figure controlling for vehicle size and horsepower/weight (a proxy for acceleration) and the right figure further controlling for year, segment, and ownership type fixed effects. Panel B shows the relationship between prices and the APEAL with the same controls. The tight correlations between price and the IQS/APEAL indicators provide strong evidence that these are credible measures of vehicle quality, with high-quality models consistently commanding high prices.

Worker flow and Supplier network To measure worker movement between firms, we collect data on the employment history of all past and current employees in the Chinese auto industry who are registered on LinkedIn (China). The data contain 52,898 LinkedIn users who have worked in JVs and domestic firms. The spatial distribution of LinkedIn users in a province reflects the production patterns across provinces well: it has a correlation of 0.89 with the provinces' automobile production in 2018.

Data on the auto parts suppliers is compiled from MarkLines's Who Supplies Whom database. Since data at the annual level are sparse, we pool information from all years. Our final sample covers 1,378 distinct part suppliers, 271 vehicle parts under 31 part categories, and 459 vehicle models. While the data are not complete enough to be regarded as a census of suppliers, they provide valuable information on the production network. These datasets allow us to examine worker flows and supplier overlap as mechanisms of knowledge spillovers. Online Appendix Section A.2 provides more details.

Geographic location of auto plants We identify the plant locations of each firm using information from auto firms' official websites (Table E.2). Figure E.5 shows that a partial overlap between the ownership network and geography. For example, Dongfeng, one of the largest affiliated SOE firms, has a plant in the same city, Wuhan, as one of its JVs' plants (Honda–Dongfeng). It also has a plant in Liuzhou, which does not host any of its JVs. At the same time, Geely, a private firm with no JV affiliation, has a plant in Shanghai, which hosts two joint ventures (VW–SAIC and GM–SAIC). Our empirical analysis explores this partial overlap between ownership and geographical networks to assess the role of both in mediating knowledge flow.

Patent transfers and licensing Data on patent transfers are collected by China's State Intellectual Property Office and cover the universe of patent transfers and licensing between firms registered in China from 2001 to 2018. This information allows us to examine the extent of direct technology payments, as

[11] They are interior, exterior, storage and space, audio/entertainment/navigation, seats, heating/ventilation/air conditioning, driving dynamics, engine/transmission, visibility and driving safety, and fuel economy. The APEAL study includes items such as "smoothness of gearshift operation" (engine/transmission), "braking responsiveness/effort" (driving dynamics), and "interior materials convey an impression of high quality" (interior).

opposed to knowledge spillovers, between JVs and domestic firms.

Consumer and household surveys We complement the above datasets with two consumer surveys and a nationally representative household survey to assess alternative demand-side mechanisms. The consumer surveys, described in detail in Appendix C, are designed to measure consumers' awareness of the JV partnerships. The household survey, conducted annually by the China National Information Center, asks each household to report the vehicle purchased and alternative models considered. These choices inform whether JVs and affiliated domestic firms target the same groups of consumers.

2.4 Descriptive Quality Upgrade Patterns

We begin by documenting descriptive quality upgrading patterns across ownership types. J.D. Power's raw IQS scores report malfunction rates of parts and components and represent an objective measure of vehicle performance.[12] Figure 2 plots the dramatic improvement in the overall IQS score during the sample period, summed across all nine quality dimensions, for JVs, affiliated SOEs, and nonaffiliated domestic automakers, respectively (a smaller number of defects indicates higher quality). At the beginning of our sample period, JVs had significantly higher quality than the other two carmaker types: the number of defects per 100 vehicles was 276 for JV models between 2001 and 2003, in contrast to 485 for models produced by affiliated domestic firms and 348 for those produced by nonaffiliated domestic firms. By 2014, the overall IQS score of the domestic models had largely converged to that of JVs: the number of defects per 100 vehicles was 95 for JV models, 123 for models from affiliated domestic firms, and 133 for those from nonaffiliated automakers. Appendix B.1 follows Foster, Haltiwanger, and Syverson (2008) to decompose the overall quality improvements into contributions by continuing models, new model entries, and old model exits. Quality improvements for both JVs and domestic firms were primarily driven by quality upgrades in continuing models, followed by the entry of new models.

Table 1 reports the summary statistics of IQS and APEAL scores by year and ownership type for each of the quality dimensions. Since the raw IQS (the malfunction rates) and APEAL scores differ substantially in magnitude across quality dimensions, we separately standardize the responses for each of the IQS survey questions and APEAL questions using all model-year observations. Then, we aggregate the standardized z-scores to the nine IQS dimensions and ten APEAL dimensions. There is significant heterogeneity in quality performance across different dimensions among firms within an ownership type, a key source of variation that we exploit in our empirical strategy.

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

3 Empirical Strategy

3.1 Empirical Framework

The goal of our empirical analysis is to identify knowledge spillovers induced by the ownership affiliation stipulations under *quid pro quo* beyond any industry-wide spillovers and quality improvements. If the domestic partners in JVs were randomly assigned, comparing the quality of vehicles produced by affiliated and nonaffiliated domestic firms before and after the JV formation would identify the effects of *quid pro quo*. However, there are two key identification challenges in our empirical setting. First, domestic firms did not introduce indigenous brands until *after* the JV formation; as a result, we cannot observe their quality before the JV formation. Second, the selection of domestic partners may not be random. For example, all the affiliated domestic partners are SOEs, which could have different baseline quality, production capability, and upgrading dynamics from the nonaffiliated firms.

To confront these empirical challenges, we propose a novel identification strategy that exploits the multi-dimensional quality measures *within* firm-product. Our research design follows a simple intuition: if there are additional spillover benefits through ownership affiliation, then the affiliated domestic automakers would more likely adopt the quality strengths of their JV partners than nonaffiliated domestic firms. For example, German brands such as BMW, Mercedes-Benz, and Volkswagen are often associated with high quality in engine performance, driving dynamics, and safety. If models produced by their affiliated domestic automakers exhibit higher quality in these same dimensions than nonaffiliated models, *ceteris paribus*, that is indicative of knowledge spillovers via ownership affiliation.[13]

Figure 3 illustrates this with a specific example. It shows the engine quality and interior quality of four models, two from JVs (BMW–Brilliance and Toyota–FAW) and two from the affiliated domestic automakers (Brilliance and FAW). The JV model from BMW–Brilliance has stronger engine performance but is weaker in interior quality than the model from Toyota–FAW. The two domestic models produced by Brilliance and FAW exhibit similar relative strengths, consistent with knowledge spillovers from JVs to their affiliated domestic firms.

To examine such patterns systematically, we implement a two-step analysis. First, we measure the relative strength of each model by partialing out a rich set of fixed effects that control for common unobservables that affect quality. We do this separately for JV and domestic models. Specifically, we construct the residualized (i.e., relative) quality score for model i in vehicle segment s for quality dimension k in year t by partialing out fixed effects for model-year it (e.g., BMW–Brilliance X3 in 2014)

[13] One could micro-found this intuition using a model in which domestic firms choose how much to invest in each quality dimension for a given product and incur a cost in doing so. Spillovers from the affiliated JVs lower the costs of quality upgrades, and such benefits are larger the stronger the leader is in a given quality dimension (or the wider the quality gap is between the leader and follower). In equilibrium, ceteris paribus, affiliated domestic firms would invest more in quality dimensions that the JV partner is stronger at, relative to nonaffiliated domestic firms and relative to the firm's investments in other quality dimensions. This then translates into shared relative quality strengths between the affiliated pairs, which we exploit in the empirical identification.

and segment-dimension-year skt (e.g., engine of small-medium SUV in 2014):[14]

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

where model-by-year fixed effects (λ_{it}) absorb the overall quality of each model and any time-varying changes. This accounts for the fact that models produced by affiliated SOEs may be on different quality trajectories from nonaffiliated models due to the selection of the JVs. The segment-dimension-year fixed effects (λ_{skt}) capture the differential trends of quality improvement across vehicle segments. For example, it allows for greater engine power of SUVs compared to sedans and accounts for industry-wide improvements in engine performance over time.[15] We also examine the robustness of our results using alternative combinations of fixed effects. The residual $\widetilde{\text{Score}}_{ikt}$ captures model i's relative strength in a quality dimension k in year t and is the focus of our second-step analysis.

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

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

where $\text{DM}\widetilde{\text{Score}}_{ikt}$ and $\text{JV}\widetilde{\text{score}}_{jkt}$ are residualized scores for model pair $\{i, j\}$ in year t and quality dimension k that we obtain via Equation (1). Z_{ij} is a vector of pair attributes, such as whether the pair is produced by affiliated firms (i.e., a domestic automaker and its affiliated JVs), belongs to the same vehicle segment, or is produced in the same province. This pairwise design allows us to examine heterogeneity in knowledge spillovers among different model pairs, with the key regressor being the dummy on JV affiliation. Standard errors are two-way clustered at i's firm and quality category (IQS or APEAL) and j's firm and category level to account for any arbitrary cross-sectional and temporal correlation of different scores within the same quality category and across models in the same firm.

We highlight two features of our empirical strategy. First, our empirical framework represents a significant departure from the approaches used in the existing literature on knowledge spillovers from FDI to domestic firms, which mainly rely on TFP variation at the industry level along with the inclusion of standard panel fixed effects (e.g., Haddad and Harrison (1993); Aitken and Harrison (1999); Javorcik (2004); Keller and Yeaple (2009)). On the one hand, our strategy addresses some of the classical

[14] To ease interpretation, we multiply the raw IQS scores by negative one, so that a larger IQS number (e.g., a less negative number) implies better quality (fewer defects).

[15] This rich set of controls absorbs industry-wide quality improvements. Therefore, if spillovers from JVs benefit both affiliated automakers and nonaffiliated automakers by the same magnitude, the estimate of β_1 does not capture this—rightly so—as industry-wide spillovers do not pertain to ownership affiliation and thus should not be counted as the benefit due to *quid pro quo*.

identification concerns in the FDI literature where the standard panel fixed effects may be inadequate in controlling for industry-time-level shocks that affect both the entry of foreign firms and the performance of domestic firms (such as government policies targeting certain industries). By focusing on different dimensions of quality strength *within* a product-year, our analysis explores a much finer level of variation and allows us to control for *time-varying* unobservables at the firm and product level. On the other hand, the quality-based measures might not fully capture gains in production efficiency, focusing instead on margins that are specific to quality improvements.[16] We recognize the strengths and limitations of different approaches and view our approach as complementary to the existing TFP-based approach to studying FDI spillovers.

Second, the two-step approach allows us to control for the time-varying average quality of the domestic and JV models separately. It is identical to the standard one-step estimation where one regresses followers' quality measures on leaders' quality measures directly and controls for appropriate "pair-wise" fixed effects in the specifications without interaction terms ($\text{JVScore}_{jkt} \times \text{Z}_{ij}$). With interaction terms, the standard one-step approach would project the entire interaction term on fixed effects, while our approach maintains the property that the interaction terms use *relative* quality strength, which is desirable for our purpose. We present the main results based on the two-step estimation procedure and perform robustness checks with the standard one-step fixed effect model in Section 4.2.

3.2 Relative Strengths of JV Models

Before we move to the main analysis, we test a key premise for our empirical analysis: models produced by different JVs indeed exhibit differential quality strengths from which domestic firms can potentially learn. Figure 4 graphically illustrates JV models' quality variation along three performance dimensions: driving dynamics, engine, and fuel efficiency. It is evident that firms have different comparative advantages. For example, models by VW–FAW and Hyundai–BAIC enjoy better driving dynamics. VW–FAW and BMW–Brilliance have more powerful and reliable engines. Nissan–Dongfeng excels at fuel efficiency. These patterns are consistent with the common perception that German brands have strong engine performance while Japanese brands are more fuel efficient.

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

[16]To elaborate this, any cost-side spillovers that correspond to quality improvements in various dimensions can, in principle, be reflected in a firm's relative quality strength. For example, through shared parts suppliers of the powertrain system, an affiliated domestic firm may benefit from lower costs of improving its engine performance. Ceteris paribus, the firm would invest more to enhance its engine performance, thereby exhibiting a relative strength in engine.

framework is capable of identifying relative strength among products within the same JV firm, we can use it to examine the similarity in relative quality strengths between JV and domestic models.

Column (1) of Table 2 shows a significantly positive interaction term between LeaderScore and SameFirm, indicating that models produced by the same firm exhibit similar quality strength.[17] Column (2) adds additional interactions with the SameSegment dummy. Interestingly, we see that relative quality strength is most similar among models in the same vehicle segment made by the same firm, as indicated by the triple-interaction term. The estimates imply that a reduction of 10 defects in a JV model is associated with a reduction of 5.8 defects for models in the same segment by the same firm, compared to 1.6 defects for models in a different segment.[18] Columns (3) to (6) partial out different combinations of firm-year, model, and model-year fixed effects. The estimates are stable across the different columns.

To understand the source of a JV's relative quality strength, we collected analogous quality measures for the U.S. market from J.D. Power and employed the same empirical strategy to analyze the quality similarity between models sold in the U.S. and related JV models in China. Our U.S. dataset spans from 2008 to 2012, a period during which J.D. Power used the same version of questionnaires in both the U.S. and China. Except for Peugeot Citroen, all foreign partners of Chinese JVs produce and sell cars in the U.S. market. Table E.3 reports the results. We find that Chinese JV and U.S. models of the same foreign automaker exhibit similar relative quality strength. The similarity is more pronounced and statistically significant for related models in the same vehicle segment and is the strongest for model pairs that bear the same name.[19] These results suggest that JV models adopt the core strengths of their foreign partners. Interestingly, the similarity between related U.S. and JV models as shown in Table E.3 is less pronounced than that between models by the same Chinese JV as shown in Table 2. The Chinese and U.S. versions of the same model have different designs, suppliers, and production locations. Variations in survey implementation could also complicate cross-country comparisons.

Overall, the regression results corroborate the patterns in Figure 4. Different JV firms exhibit differential strengths across quality dimensions, and the evidence is particularly strong for models in the same segment.[20] This sets the stage for our analysis of spillovers from JVs to domestic firms.

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

[18] The correlation in relative quality strength is 0.155 - 0.062 + 0.491 = 0.584 for models in the same segment and 0.155 for models in different segments.

[19] About one-third of Chinese JV models have a U.S. counterpart with the same model name. The other JV models are specifically designed for the Chinese market and bear distinct names.

[20] Segment-specific relative strength may reflect the fact that models in different segments tend to target different consumers (Section 4.3). Models in the same segment are also more likely to be assembled in the same plant, which contributes to the quality strength through similar production processes and parts suppliers, etc. (Sections 4.3 and 5).

4 Results on Knowledge Spillovers

4.1 Main Results

Our unit of observation is a domestic–JV model pair by quality dimension by year. There are 13,946 distinct domestic–JV pairs and 723affiliated pairs. We have nineteen quality dimensions: nine IQS quality dimensions and ten APEAL performance dimensions.

Table 3 presents the estimation results for Equation (2). The coefficient on JVScore captures the association in relative quality strengths between a random pair of nonaffiliated models.[21] The SameGroup dummy flags follower–leader pairs that come from JVs and their affiliated domestic partners (e.g., Toyota–FAW and FAW). In Column (1), the coefficient on the JVScore - SameGroup interaction is positive and statistically significant, suggesting knowledge spillovers between affiliated model pairs. When we add interactions with the SameSegment dummy in Column (2), we find that spillovers occur primarily among products in the same segment (e.g., sedan or SUV), consistent with the finding from Table 2. The estimates in Column (2) of our preferred specification imply that 9.8% of the quality improvement in a JV model would be transmitted to affiliated domestic models in the same segment.[22] Another way to interpret the magnitude is to compare it with that in Column (2) of Table 2: the shared quality strength between JV–affiliated domestic pairs is 17% ($=\frac{0.098}{0.584}$) of that among the models in the same segment by the same JV firm.

One might be concerned that we over-control and under-estimate the strengths of knowledge spillovers by partialling out a rich set of fixed effects at the model-year and segment-dimension-year levels. In Columns (3) to (6), we report less demanding specifications with fixed effects for firm, firm-year, or firm-year and model. Our estimates are stable across these alternative specifications.

4.2 Robustness checks

We perform a series of robustness checks. First, we explore an alternative fixed effect regression specification. Our baseline empirical strategy is based on residualized quality measures after model-year and dimension-segment-year fixed effects are partialed out separately for leaders and followers. Table E.4 reports results from standard one-step regressions that use the same set of fixed effects as in Table 3 at the pair level (for example, model-pair-year fixed effects instead of model-year fixed effects). While these approaches are not mathematically identical, as discussed in Section 3.1, the resulting estimates

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

[22] The effective size of 9.8%=$0.016 - 0.005 + 0.087$ is the sum of coefficients for SameGroup, SameSeg, and SameGroup $\times$ SameSeg.

are very similar. Second, due to the frequent model turn-overs in the industry (only 37% of JV models and 17% of domestic models last for more than six years), we repeat our analysis using balanced panels and on a subset of models present for significant durations during the sample period (Table E.5). Results are similar to those under our baseline specification, consistent with our finding in Section 2.4 that quality improvement was primarily driven by upgrades in continuing models. Third, we show in Table E.6 that the estimate for knowledge spillovers is stable whether we use the IQS and APEAL scores separately or jointly.

We also assess potential attenuation bias due to measurement errors in our quality scores. We implement an instrumental variable (IV) analysis using two sets of quality measures constructed from randomly-chosen half samples of the underlying consumer surveys, with one set of quality measures serving as the IV for the other set. Details of the analysis are discussed in Appendix B.2. Table E.7 shows that the IV estimates are somewhat larger than the corresponding OLS estimates, but the differences are statistically insignificant via the Hausman test, thus alleviating the concern about measurement errors (Hausman, 1978).

Finally, we perform additional analyses on the statistical significance of our results. We explore alternative levels of clustering (Table E.8), calculate standard errors using bootstrap (Table E.9), and perform a permutation analysis to compare our estimate against a distribution of placebo estimates based on randomly generated placebo ownership affiliations (Section B.3 and Figure E.6). Our main estimates remain statistically significant across all tests.

4.3 Alternative Explanations

The finding that domestic models mimic the quality strengths of their affiliated JV models is consistent with knowledge spillovers via ownership affiliations. We now investigate several alternative interpretations. As spillovers occur primarily among products in the same segment as shown in Table 3, we limit the sample to follower–leader pairs in the same segment for the evaluation of alternative explanations in this sub-section and potential mechanisms in Section 5. Including follower–leader pairs in different segments does not affect the key findings.

Endogenous JV formation. One concern is that the ownership network of domestic firms forming joint ventures (JVs) with foreign automakers is not random. For instance, domestic automakers may seek foreign partners who excel in specific quality dimensions to overcome their weaknesses, potentially biasing the coefficient estimates downward and masking the evidence for knowledge spillovers. Conversely, if foreign firms choose partners with similar quality strengths, the estimates might be biased upward.

To address this, we exploit the fact that many major JVs were formed in the 1980s and 1990s when domestic automakers had virtually no passenger vehicle production capacity and experience. It would be very difficult for foreign automakers to predict the strengths/weaknesses of potential Chinese partners decades later. Appendix A.1 provides a brief history of two JVs and shows that partnership decisions were made by the central government with no evidence of considering relative quality strengths.

Column (1) of Table 4 reproduces our baseline specification in Column (2) of Table 3 using follower–leader model pairs in the same vehicle segment. Column (2) examines knowledge spillovers for JVs formed before and after 2000 and finds that spillovers are observed only for JVs formed before 2000, whose partnership choices were unlikely influenced by selection based on relative quality strengths. In Columns (3) and (4), we further examine how quality similarity depends on the age of the JVs. Column (3) shows that quality similarity is most pronounced among pairs of models with over ten years of JV relationship, with a negative though imprecise point estimate for JVs younger than 5 years. Column (4) controls for the initial correlation in relative quality strength for each affiliated pair by interacting the SameGroup dummy with dummies for each pair of affiliated firms and examines how the correlation of quality strength evolves over time *within* an affiliation. The positive and statistically significant interaction term between SameGroup and JVAge suggests that affiliated pairs of models become more similar over time, consistent with the observation that knowledge spillovers take time to materialize.[23] Overall, the results lend support to the knowledge spillovers interpretation as opposed to endogenous formation.

Spillovers due to geographic proximity. Existing literature has documented the role of geographic proximity in promoting spatially-mediated knowledge spillovers (Jaffe, Trajtenberg, and Henderson, 1993; Bloom, Schankerman, and Van Reenen, 2013). To the extent that production facilities of JVs and their affiliated domestic firms are sometimes located close to one another, the patterns of knowledge spillovers could be partly driven by geographic proximity rather than ownership affiliation per se.[24] To examine this, we exploit the *partial* overlap between the ownership and geographical networks as shown in Figure E.5. We construct a dummy for two models in the same province and interact the ownership dummies (SameGroup and DiffGroup) with the location dummies (SameProvince and DiffProvince). Column (1) of Table E.10 replicates the baseline specification. Column (2) presents the full interaction between ownership and geography dummies. While spillovers between affiliated pairs in the same province are the strongest, there remain substantial knowledge spillovers from JVs to affiliated domestic firms in *different* provinces. In addition, the spillovers between nonaffiliated pairs in the same

[23] An ideal approach to examine the evolution of knowledge spillovers over time is to conduct an event study, but this is challenging in our setting due to the complete absence of affiliated domestic production of passenger vehicles before JV formation and the fact that very few domestic firms introduced models immediately after JV formation. In Section B.4, we mimic an event study and define year zero as the year when an affiliated domestic firm introduced its first indigenous model (Figure E.7). Knowledge spillovers indeed strengthen over time but take years to occur.

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

province are positive but insignificant. These patterns provide evidence that the knowledge spillovers detected between affiliated pairs cannot be fully explained by geographic proximity.

Overlapping customer bases. The observed similarity in relative quality strength may be partially driven by demand-side factors, as opposed to knowledge spillovers. For example, models produced by affiliated automakers may be designed to target the same group of consumers who share similar taste, which then leads firms to specialize in similar quality dimensions. We leverage the household choices reported in the vehicle ownership survey (described in Section 2.3) to evaluate whether affiliated JVs and domestic automakers have overlapping customer bases (i.e., more likely to be listed together in a given consumer's top choice set). The results in Table E.11 provide no evidence that affiliated model pairs are more likely to attract similar customers than a random pair of JV and domestic models. This is not surprising given that JV models are considerably more expensive than domestic indigenous models and target wealthier households.

Brand image association. Another potential explanation for the observed knowledge spillovers is brand image association. Brand association can influence consumers' perception of product quality. For example, consumers might perceive Brilliance to excel in engine performance simply because it has a joint venture with BMW (BMW-Brilliance). Consequently, firms might strategically invest in certain quality dimensions to leverage the brand image association and capitalize on consumer perceptions, regardless of actual knowledge spillovers. To examine this possibility, we conduct additional consumer surveys to gauge consumers' awareness of JV affiliations by asking them to identify affiliated partners from a list of domestic and foreign firms. Appendix C describes the surveys and results in detail. We find significant variations in brand awareness between different JVs: for example, 74% of consumers identified BMW-Brilliance affiliation, while only 7% recognized PSA-Changan. Exploring this heterogeneity, we show in Table E.12 that stronger JV recognition does not translate into greater similarity in quality strength. These findings alleviate the concern that either perception or strategic investment through brand image associations drives the shared relative quality strength between affiliated partners.

Direct payments for technologies. The identified spillover effect might be driven by market transactions. For example, technologically advanced firms might sell or license their patents to firms that lack the capacity to conduct R&D in-house. To examine this, we obtain data on the universe of patent transfers and licensing between any registered firms in China from the National Intellectual Property Administration.[25] For the period between 2001 and 2019, there are 1,208,325 records of patent transfers and licensing nationwide, of which 10,626 involve firms in the auto industry (i.e., either the transferor

[25] The data does not capture any patent transfer or licensing from a foreign firm (e.g., GM in the US) to a Chinese JV (e.g., GM-SAIC). However, it captures any patent transfer or licensing originating from a JV to any other domestic firms in China, which is the focus of the empirical analysis examining knowledge spillovers from JV to domestic firms.

or the transferee is owned by an auto assembly firm). Among the 10,626 cases, only 27 cases originated from a JV. The lack of direct patent transfer and licensing from JVs to domestic firms is consistent with the finding in Holmes, McGrattan, and Prescott (2015) that JVs file a small number of patent applications in China in comparison to either domestic firms or foreign multinationals. Therefore, the observed patterns of spillovers are unlikely to be driven by market transactions of technologies.

In sum, we have shown that domestic models share similar quality strengths with affiliated JV models. The investigation on a host of alternative explanations supports the interpretation of knowledge spillovers via the ownership network. Next, we investigate the potential underlying mechanisms.

5 Potential Mechanisms of Knowledge Spillovers

The vehicle production process encompasses interconnected stages from product planning to design and engineering, parts sourcing, testing, and assembly. This process involves intricate interactions of technologies, equipment, and workers, where knowledge spillovers could occur at various stages and through multiple channels, including deliberate communication among partners, worker exchanges, or shared parts suppliers. To shed light on the underlying channels of knowledge spillovers, we begin by examining the impact of past production experience. We measure firm-level cumulative production using vehicle sales data going back to 1992 (the historical sales data are only available at the firm level, not by segment). For each firm-year, we calculate the total number of vehicles the firm has sold up to the previous year. We examine how cumulative production by the JV and domestic firm influences the intensity of knowledge spillovers. Table E.13 presents the result. Knowledge spillovers become stronger as the cumulative JV production increases but appear to be unaffected by cumulative production by the affiliated domestic firm. While suggestive, the results indicate that knowledge spillovers likely occur through the domestic partner's observation and assimilation of the JV's production processes. Once this occurs, affiliated domestic firms seem to rely less on their own experiential "learning-by-doing."

Next, we examine the role of worker flows and supplier networks in mediating knowledge spillovers, focusing on pairs of domestic and JV models in the same vehicle segment. To measure worker flows, we compile job switches from user profiles on LinkedIn (China) for the automobile sector and count the number of job switchers between each pair of JV and domestic firms. For supplier network, we use the MarkLines data and compute the Szymkiewicz–Simpson overlap ratio for each model pair, which equals the number of common suppliers divided by the smaller number of suppliers among the two. For both worker flows and supplier overlap, we standardize the measures across all observations and interact the standardized measures with the SameGroup dummy. Table E.14 summarizes the results. Column (1) replicates the baseline specification for model pairs in the same segment. Columns (2) and (3) examine the importance of worker flow and supplier overlap separately, while Column (4) combines them in one regression analysis. Overall, increased worker flow is associated with stronger knowledge spillovers to both affiliated firms and nonaffiliated firms, with an even larger effect for the former. High supplier overlap also predicts stronger knowledge spillovers, but the additional effect from ownership affiliation is small and imprecisely estimated. To the extent that affiliated domestic and JV firms have greater worker flows and supplier overlap, estimates in Column (4) suggest that worker flow accounts for 34% of knowledge spillovers from JV to affiliated domestic firms, while supplier overlap explains 14%.[26,27]

We acknowledge several limitations of the mechanism analyses. Since the variations in worker flows and supplier networks are not necessarily exogenous, the evidence does not have a causal interpretation. Additionally, both LinkedIn and Markline data cover only a selected sample of worker flows and part suppliers. Nevertheless, the findings are broadly consistent with the FDI literature, which highlights the importance of worker flows as carriers of knowledge (e.g., Poole (2013); Stoyanov and Zubanov (2012)) and shared suppliers in facilitating backward spillovers and knowledge flow (e.g., Kee (2015)).

6 Impact of *Quid Pro Quo* on Domestic Upgrades

We conclude our analysis by discussing the magnitude of knowledge spillovers through *quid pro quo* and its impact on the quality of domestic vehicles. Our estimates indicate that the shared quality strength between affiliated JV and domestic pairs is 17% ($= \frac{0.098}{0.584}$) of that between models produced by the same JV firm. This fraction increases to 28% ($= \frac{0.145}{0.515}$) for JVs formed before 2000.[28] These results suggest that affiliated domestic firms adopted a substantial portion of the core strengths of their foreign partners, though knowledge spillovers do not fully transmit the core strengths.

Our empirical identification relies on relative quality strengths between followers (domestic models) and leaders (JV models). Assuming that knowledge spillovers are proportional to the average JV quality and the initial quality of affiliated domestic models, *quid pro quo* contributes 8.3% of the quality improvement experienced by affiliated domestic models between 2001 and 2014, equivalent to a reduction of 31 defects per model.[29] This is on top of any industry-wide spillovers due to the presence of foreign firms. Appendix D provides more details.

[26] Among all workers who switched jobs from a JV to a domestic firm, 27.2% moved to the JV's affiliated domestic firm. This fraction would have been 9.3% if worker movements were random. For suppliers, affiliated model pairs share on average 12 common suppliers, in comparison to the average of 5.4 common suppliers between nonaffiliated pairs.

[27] For worker flows, the difference in the average z-scores of an affiliated and a nonaffiliated pair is 1.23. Additional worker flow from JVs to affiliated automakers contributes $1.23 \times 0.027 = 0.033$ or 34% of knowledge spillovers (the baseline is 0.098 in Column (2) of Table 3). For supplier overlap, the difference in the average supplier overlap z-scores of an affiliated and a nonaffiliated pair is 0.91. Additional supplier overlap contributes $0.91 \times 0.015 = 0.014$ or 14% of knowledge spillovers.

[28] The estimate of 0.515 is the sum of coefficients for SameFirm, SameSeg, and SameFirm × SameSeg when we replicate the analysis in Column (2) of Table 2 using a subsample of JVs formed before 2000.

[29] The average JV quality is 179 defects from 2001-2014. Affiliated domestic models had 498 defects in 2001 but experienced a reduction of 375 defects from 2001-2014. Knowledge spillovers contribute $|(179 - 498)| \times 0.098 = 31$ fewer defects, or 8.3% of quality improvement. This calculation uses 0.098, which is the sum of coefficients for SameGroup, SameSeg, and SameGroup × SameSeg in our preferred specification, Column (2) of Table 3. The effect size is nearly identical if we use the average defects in 2001-2003 instead of 2001 for affiliated domestic models.

We acknowledge several caveats of our quantification analyses and discuss general policy takeaways. First, as discussed in Section 3, our analysis does not fully capture the entirety of cost-side spillovers and gains in production efficiency that do not directly contribute to quality improvements. Nonetheless, quality upgrading is seen as a crucial driver of economic growth and a key policy goal for developing countries, especially in high-tech sectors. Second, our empirical strategy aims to identify the benefits to affiliated domestic firms beyond the industry-wide spillovers induced by the presence of foreign firms under *quid pro quo*. Consequently, our findings pertain only to the partial benefits of *quid pro quo* and the benefits to overall domestic industrial quality upgrades could be larger.

The focus on spillovers via JV affiliation directly addresses the recent policy of lifting the JV requirement while still allowing foreign automakers to operate in China. We conjecture that this policy change would not significantly hinder domestic upgrading moving forward, considering that the quality gap between domestic firms and JV firms had significantly narrowed by 2014 (Figure 2). Furthermore, the evidence in Section 5, although suggestive, underscores the importance of market-based mechanisms in facilitating knowledge spillovers, which would continue organically in the absence of the JV stipulation.

7 Conclusion

This paper examines the effect of *quid pro quo* – the policy of requiring technology transfer through joint ownership in exchange for market access – on knowledge spillovers. We document consistent patterns of knowledge spillovers from JVs to affiliated domestic automakers beyond industry-wide spillovers. Several unanswered questions remain and can be explored in future research. First, our study focuses on the benefits of *quid pro quo* for affiliated domestic firms but does not address the costs to foreign firms, including potential IP infringement risks. Second, the analysis does not examine the historical efficacy of *quid pro quo*, i.e., what would have happened had China not implemented the policy from the beginning. Last but not least, our analysis focuses on spillovers to domestic automakers based on the existing set of products and technologies introduced by foreign automakers, abstracting away from potential endogenous changes in product offerings in the absence of *quid pro quo*. With a majority stake or sole ownership, foreign automakers may have stronger incentives to bring the most advanced technology to China and offer a different set of products especially when the risks of expropriation and involuntary technology spillovers are deemed to be small. Exploring how policies and global knowledge spillovers affect foreign firms' incentives to innovate and introduce technologies to host countries remains an important area for future research.

References

Abebe, Girum, Margaret McMillan, and Michel Serafinelli. 2022. "Foreign direct investment and knowledge diffusion in poor locations." Journal of Development Economics 158:102926.

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

Alfaro-Urena, Alonso, Isabela Manelici, and Jose P Vasquez. 2022. "The effects of joining multinational supply chains: New evidence from firm-to-firm linkages." The Quarterly Journal of Economics 137 (3):1495–1552.

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

Bai, Jie, Maggie Chen, Jin Liu, and Daniel Yi Xu. 2020. "Search and Information Frictions on Global E-Commerce Platforms: Evidence from AliExpress." Tech. rep., National Bureau of Economic Research.

Barwick, Panle Jia, Myrto Kalouptsidi, and Nahim Bin Zahur. 2024. "China's Industrial Policy: an Empirical Evaluation." Review of Economic Studies Forthcoming.

Bilir, L. Kamran and Eduardo Morales. 2020. "Innovation in the Global Firm." Journal of Political Economy 128 (4):1566–1625.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying technology spillovers and product market rivalry." Econometrica 81 (4):1347–1393.

Branstetter, Lee and Kamal Saggi. 2011. "Intellectual property rights, foreign direct investment and industrial development." The Economic Journal 121 (555):1161–1191.

Buera, Francisco J. and Ezra Oberfield. 2020. "The Global Diffusion of Ideas." Econometrica 88 (1):83–114.

Cauley, Jon and Todd Sander. 1992. "Agency theory and the Chinese enterprise under reform." China Economic Review 3 (1):39–56.

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

Chen, Yuyu, Mitsuru Igami, Masayuki Sawada, and Mo Xiao. 2021. "Privatization and productivity in China." The RAND Journal of Economics 52 (4):884–916.

Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and taxation: Theory and evidence." American economic review 99 (4):1145–1177.

Eaton, Jonathan and Mark Gersovitz. 1984. "A Theory of Expropriation and Deviations from Perfect Capital Mobility." The Economic Journal 94 (373):16–40.

Fons-Rosen, Christian, Sebnem Kalemli-Ozcan, Bent E Sorensen, Carolina Villegas-Sanchez, and Vadym Volosovych. 2017. "Foreign investment and domestic productivity: Identifying knowledge spillovers and competition effects." Tech. rep., National Bureau of Economic Research.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?" American Economic Review 98 (1):394–425.

Giorcelli, Michela. 2019. "The long-term effects of management and technology transfers." American Economic Review 109 (1):121–52.

Groves, Theodore, Yongmiao Hong, John McMillan, and Barry Naughton. 1994. "Autonomy and Incentives in Chinese State Enterprises." The Quarterly Journal of Economics 109 (1):183–209.

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

Hansman, Christopher, Jonas Hjort, Gianmarco León-Ciliotta, and Matthieu Teachout. 2020. "Vertical integration, supplier behavior, and quality upgrading among exporters." Journal of Political Economy 128 (9):3570–3625.

Harrison, Ann and Andrés Rodríguez-Clare. 2009. "Trade, foreign investment, and industrial policy for developing countries." Handbook of Development Economics 5:4039–4214.

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

Hausman, Jerry A. 1978. "Specification tests in econometrics." Econometrica: Journal of the econometric society :1251–1271.

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

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

Jaffe, Adam, Manuel Trajtenberg, and Rebecca Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." Quarterly Journal of Economics 108 (3):577–598.

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

Jefferson, Gary H. 1998. "China's State Enterprises: Public Goods, Externalities, and Coase." The American Economic Review 88 (2):428–432.

Jiang, Kun, Wolfgang Keller, Larry D Qiu, and William Ridley. 2018. "International joint ventures and internal vs. external technology transfer: Evidence from China." Tech. rep., National Bureau of Economic Research.

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

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

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

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

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

Konrad, Kai A. and Kjell Erik Lommerud. 2001. “Foreign direct investment, intra-firm trade and ownership structure.” European Economic Review 45 (3):475–494.

Kosova, Renata. 2010. “Do foreign firms crowd out domestic firms? Evidence from the Czech Republic.” The Review of Economics and Statistics 92 (4):861–881.

Lane, Nathan. 2022. “Manufacturing revolutions: Industrial policy and industrialization in South Korea.” Available at SSRN 3890311 .

Lin, Justin Yifu, Fang Cai, and Zhou Li. 1998. “Competition, Policy Burdens, and State-Owned Enterprise Reform.” The American Economic Review 88 (2):422–427. URL http://www.jstor.org/stable/116960.

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

Macchiavello, Rocco and Josepa Miquel-Florensa. 2019. “Buyer-driven upgrading in gvcs: The sustainable quality program in Colombia.” CEPR Discussion Paper No. DP13935 .

McCaig, Brian, Nina Pavcnik, and Woan Foong Wong. 2020. “FDI inflows and domestic firms: Adjustments to new export opportunities.” NBER Working Paper.

Medina, Pamela. 2022. “Import Competition, Quality Upgrading, and Exporting: Evidence from the Peruvian Apparel Industry.” The Review of Economics and Statistics :1–45.

Muller, Thomas and Monika Schnitzer. 2006. “Technology Transfer and Spillovers in International Joint Ventures.” Journal of International Economics 68 (2):456–468.

Naughton, Barry. 1995. Growing out of the Plan: Chinese Economic Reform. Cambridge University Press.

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

Schnitzer, Monika. 2002. “Debt v. Foreign Direct Investment: The Impact of Sovereign Risk on the Structure of International Capital Flows.” Economica 69 (273):41–67.

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

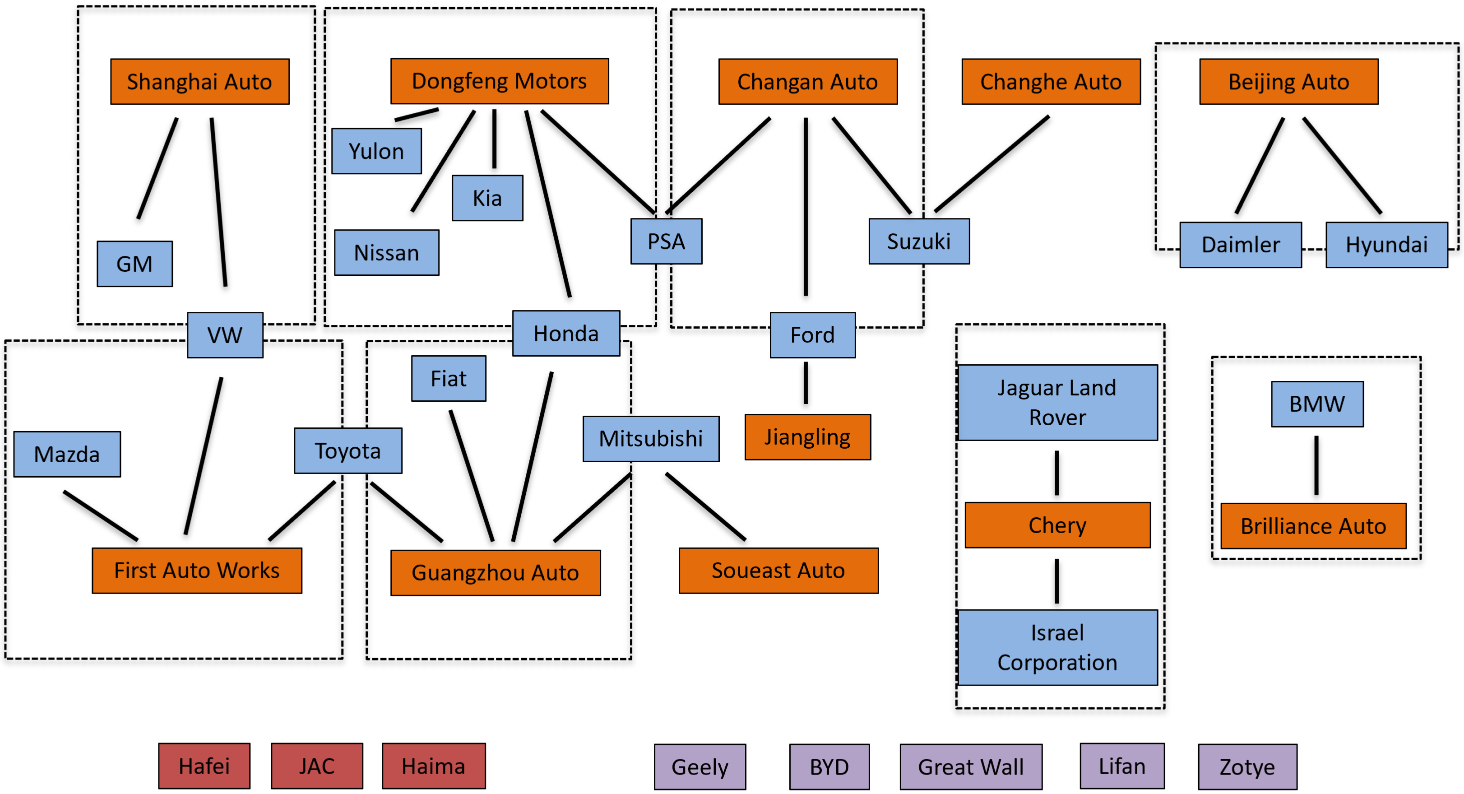
UNCTAD. 2018. World investment report 2018: Investment and new industrial policies. UN.

Verhoogen, Eric. 2023. “Firm-Level Upgrading in Developing Countries.” Journal of Economic Literature 61 (4):1410–64.

Wollmann, Thomas G. 2018. “Trucks without bailouts: Equilibrium product characteristics for commercial vehicles.” American Economic Review 108 (6):1364–1406.

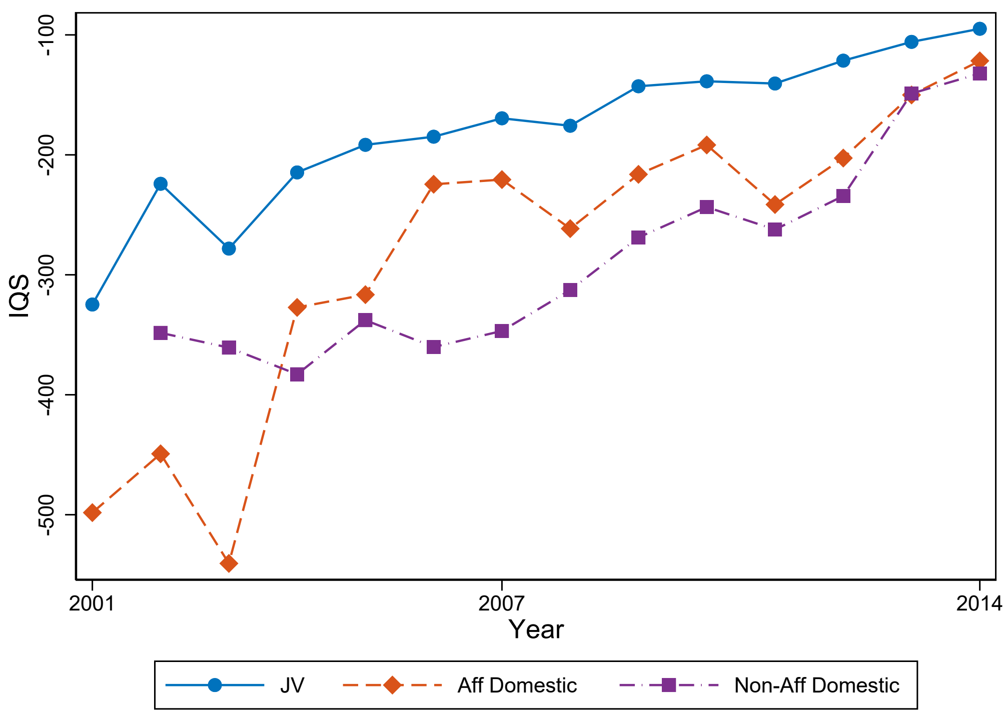
World Bank. 2018. Global investment competitiveness report 2017/2018: Foreign investor perspectives and policy implications. World Bank Washington, DC.

Figure 1: Joint Venture Network of the Chinese Auto Industry



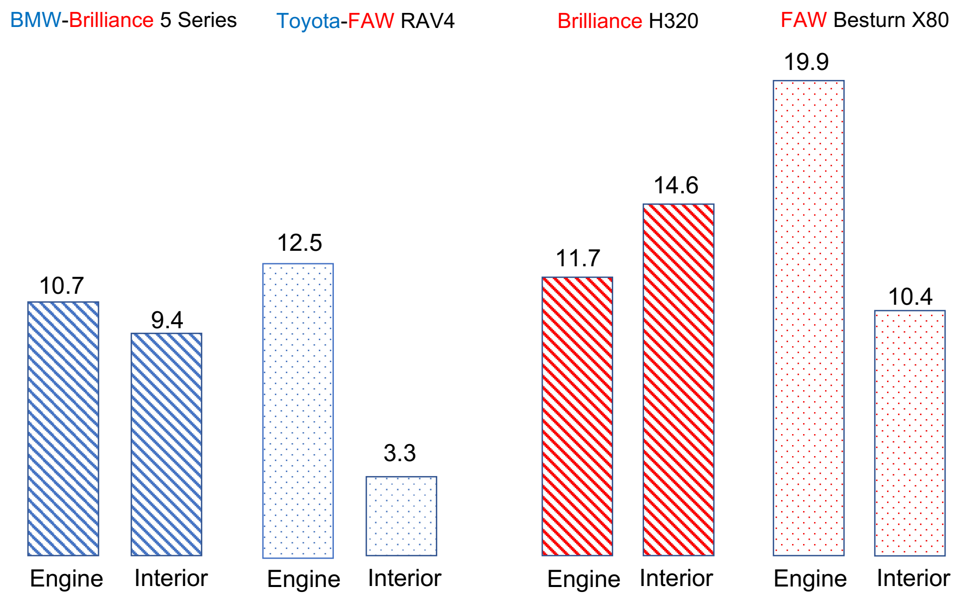
Notes: This figure, adapted from Figure 1 in Chen, Lawell, and Wang (2020), illustrates the joint venture network of the Chinese auto market as of 2014. Orange boxes represent affiliated state-owned enterprises (SOEs), blue boxes represent foreign or Taiwanese partners in joint ventures (JVs), red boxes represent non-affiliated SOEs, and purple boxes represent private domestic automakers. Dashed lines indicate groups of JVs that share the same affiliated domestic SOE. All affiliated SOEs, except for Changhe Auto, Jianglin, and Soueast, had independent indigenous models tracked by J.D. Power. FAW Auto Works has subsidiaries FAW Xiali and FAW Jilin, Dongfeng Motors has a subsidiary Dongfeng Liuzhou, and Guangzhou Auto has a subsidiary GAC Changfeng. GM-Shanghai also operates GM-Shanghai-Wuling. Two small JVs, Lotus-Youngman and Fiat-Nanjing, are omitted from the graph, and their domestic partners did not have independent passenger vehicle productions. Haima was initially founded in 1992 as a JV between Hainan provincial government and Mazda to produce Mazda models for sale in China. The JV ended in 2006 when Mazda transfer all its share of Haima to FAW. Hafei was acquired by Changan Auto in 2009.

Figure 2: Descriptive Patterns of Quality Upgrades



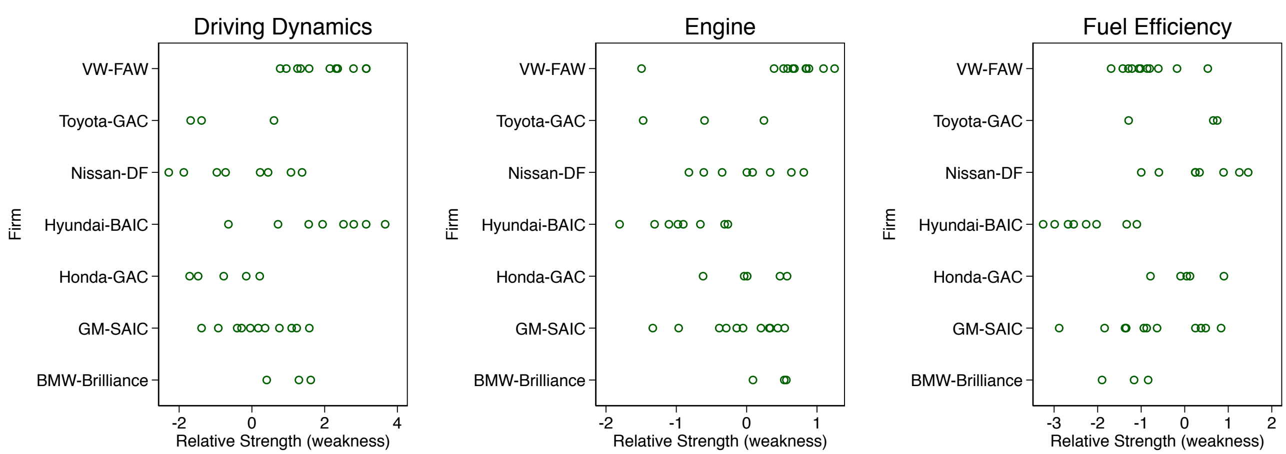
Notes: The vertical axis reports the IQS score, which is the total number of problems experienced per 100 vehicles during the first 90 days of ownership across nine performance dimensions. We show the average IQS score across all models of each ownership type. We multiply the IQS score with -1 so that higher values along the y-axis indicate higher quality (for example, -100 denotes a better quality than -300).

Figure 3: Leader–Follower Pattern of Relative Quality Strength



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

Figure 4: Differential Relative Quality Strengths among Leaders



Notes: This figure shows relative quality strengths (after model-year and quality-dimension-segment fixed effects are partialed out) across JVs along three vehicle performance dimensions measured in the APEAL, namely, driving dynamics, engine and fuel efficiency. A higher value indicates higher quality. Each circle represents a model produced by a given automaker. The sample includes vehicle models in all segments in 2014.

Table 1: Summary Statistics: IQS and APEAL Scores

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

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

Table 2: Relative Quality Strength among JVs

	(1)	(2)	(3)	(4)	(5)	(6)
Leader Score	-0.021***	-0.009***	-0.031***	-0.023***	-0.031***	-0.027***
	(0.001)	(0.002)	(0.005)	(0.003)	(0.004)	(0.003)
× SameFirm	0.305***	0.155***	0.182***	0.103***	0.181***	0.172***
	(0.035)	(0.040)	(0.049)	(0.031)	(0.044)	(0.035)
× SameSeg		-0.062***	0.054**	0.029**	0.056**	0.035**
		(0.004)	(0.023)	(0.015)	(0.023)	(0.013)
× SameFirm × SameSegment		0.491***	0.445***	0.499***	0.442***	0.466***
		(0.037)	(0.034)	(0.037)	(0.036)	(0.032)
Observations	794,494	794,494	813,875	813,875	813,875	813,875
Partialling out:						
Model-year FE	✓	✓				✓
Dimension-Segment-Year FE	✓	✓				
Firm FE			✓			
Firm-year FE				✓		
Model FE					✓	
Dimension-year FE			✓	✓	✓	✓
Dimension-Segment FE			✓	✓	✓	✓

Notes: We randomly assign each JV model to be either a follower or a leader (with a 50% chance each) and match each leader and follower into pairs. The dependent variable is the quality score of a follower model. The unit of observation is a model pair-year-quality dimension. Both leader and follower scores are residualized scores after the set of fixed effects specified under each column is partialed out. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1. Models produced by the same JV firm have similar comparative advantages, but this association is much stronger for models by the same JV and within the same segment than models by the same JV but in different segments.

Table 3: Knowledge Spillovers from JVs to Domestic Firms

	(1)	(2)	(3)	(4)	(5)	(6)
JVScore	-0.002	-0.001	-0.008***	-0.006***	-0.009***	-0.007***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
× SameGroup	0.032**	0.016	-0.001	0.004	0.017	0.006
	(0.016)	(0.012)	(0.039)	(0.025)	(0.041)	(0.031)
× SameSeg		-0.005***	0.043**	0.029***	0.040**	0.033***
		(0.001)	(0.017)	(0.010)	(0.018)	(0.009)
× SameGroup × SameSeg		0.087***	0.108***	0.090**	0.116***	0.112***
		(0.028)	(0.038)	(0.034)	(0.042)	(0.035)
Observations	717,500	717,500	738,948	738,948	738,948	738,948
Partialing out:						
Model-year FE	✓	✓				✓
Dimension-Segment-Year FE	✓	✓				
Firm FE			✓			
Firm-year FE				✓		
Model FE					✓	
Dimension-year FE			✓	✓	✓	✓
Dimension-Segment FE			✓	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We consider all pairs of models produced by JVs and domestic automakers. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after various fixed effects are partialed out. SameGroup equals 1 if the two models belong to a pair of affiliated automakers. SameSeg equals 1 if the two models belong to the same vehicle segment. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1. Our preferred specification is Column (2) with model-year and dimension-segment-year fixed effects.

Table 4: Results on Endogenous JV Formation

	(1)	(2)	(3)	(4)
JVScore	-0.006*	-0.006*	-0.006*	-0.006
	(0.003)	(0.003)	(0.003)	(0.004)
× SameGroup	0.097***			
	(0.030)			
× SameGroup × JV Formed before 2000		0.145***		
		(0.039)		
× SameGroup × JV Formed after 2000		-0.014		
		(0.037)		
× SameGroup × (JV Age ∈ [0,5])			-0.120	
			(0.074)	
× SameGroup × (JV Age ∈ (5,10])			0.001	
			(0.033)	
× SameGroup × (JV Age > 10)			0.131***	
			(0.033)	
× SameGroup × JV Age				0.023**
				(0.009)
Observations	138,540	138,540	138,540	138,540
Partialing out:				
Model-year FE	✓	✓	✓	✓
Dimension-Segment-Year FE	✓	✓	✓	✓
Control for:				
Baseline correlation in quality strength				✓

Notes: The dependent variable is the quality score of a domestic model. We focus on pairs of models produced by JVs and domestic automakers in the same segment. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after partialling out model-year fixed effects and dimension-segment-year fixed effects. JV Age is the current year minus the year when the JV was formed. In Column (4), we control for the baseline quality correlation between each JV-affiliated-domestic pair by interacting the SameGroup dummy with dummies for each pair of affiliated firms. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Appendices. For Online Publication Only

A Historical Background and Additional Data Summaries

A.1 Historical Background of JVs and the *Quid Pro Quo* Policy

Historical Background At the onset of the Chinese economic reform in 1978, Chinese leader Deng Xiaoping gave permission to the automobile industry to bring in foreign investment to develop the industry. Seeking foreign partners, China's First Ministry of Machinery, in charge of automobile production, invited major international automakers to visit China. GM was the first to send a delegation to China in October 1978. During the meeting with government officials, GM CEO Thomas Murphy put forward the idea of establishing a joint venture. Albeit a foreign concept to the Chinese hosts, the idea of using joint ventures to incentivize foreign automakers to provide technology was quickly reported to Deng Xiaoping. Deng supported the idea, which then became a longstanding industrial policy for the nation.[1] Subsequently, *quid pro quo* is implemented in other industries that are considered strategically important, including advanced manufacturing sectors such as aircraft and shipbuilding.[2]

Organizational Economics Rational for JVs While the emergence of JVs on the radar of Chinese policymakers may appear accidental, their eventual adoption as the designated form for attracting foreign investment in the automotive industry was intentional. Theoretical literature also provided important justifications for JV as an organizational form from the perspective of foreign investors and host countries.

When investing in developing countries, foreign investors are often confronted with a multitude of risks, such as confiscatory taxation, involuntary technology spillovers, and political uncertainties. The risk of not being able to repatriate any future earnings due to confiscatory taxation or the threat of expropriation by the host country can significantly deter foreign investors, leading to the hold-up program in the context of FDI (Eaton and Gersovitz, 1984). Theoretical studies have illustrated that JVs as an ownership structure can alleviate the expropriation risk and alleviate the hold-up problem relative to wholly owned foreign firms (Konrad and Erik Lommerud, 2001; Schnitzer, 2002).

Muller and Schnitzer (2006) show that whether JVs are in the interest of both host country and multinationals depends on the country- and industry-specific determinants that affect the nature of spillovers and the host country's policies, such as investment and tax incentives. When China first opened up in 1978, there were significant uncertainties regarding future policy directions, and the threat of nationalization still lingered. Foreign automakers like GM might have viewed JVs as an ownership structure that could mitigate these risks. From the perspective of the Chinese government, JVs could offer more incentives for foreign automakers to invest in China and bring better technologies

[1] Source: `https://media.gm.com/media/cn/zh/gm/news.detail.html/content/Pages/news/cn/zh/2011/Aug/0802.html`.

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

to the Chinese market. Through collaboration between domestic and foreign partners, JVs could better facilitate the exchange of knowledge, expertise, and technology.

Formation of Early JVs The first JV was set up in 1983 between American Motors Corporation (AMC, later acquired by Chrysler) and Beijing Jeep Corporation Ltd., after four years of negotiations with the involvement of the highest levels of Chinese government. According to the first Chinese manager of the JV, the initiative to form this JV was approved by Deng Xiaoping and six vice premiers. The signing ceremony took place in the Great Hall of the People, signifying the critical role played by the central government. Present during the ceremony was the Vice Premier and Minister of the Ministry of Foreign Trade and Economic Cooperation, Chen Muhua, together with other high-level government officials. The first model produced by the joint venture was the Jeep Cherokee, a popular model in the US market and chosen by Chen on her first trip to visit AMC, instead of the obsolete BJ models initially agreed upon by both parties.[3]

The second joint venture was formed in 1984 between Volkswagen (50% equity), Shanghai Tractor Corporation (25% equity), Bank of China Shanghai Trust & Consulting Company (15%), and China Automotive Industry Corporation (10%). China's central government again played a major role in the JV formation. In hopes of securing a partnership with Daimler-Benz, the Minister of the First Ministry of Machinery (Zhou Zijian) led a delegation to visit Daimler-Benz's headquarters in November 1978. When Zhou arrived in Germany, he was surprised that Volkswagen (an unknown brand to China at the time)—not Benz—was the most popular brand on the street. He decided to visit Volkswagen's headquarters, some 500 km from the original destination. The surprise visit to Volkswagen led to the VW–Shanghai JV (later renamed VW–SAIC) six years later, again with a signing ceremony in the Great Hall of the People.[4]

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

Early JV experience In the 7th Five-Year Plan (1986-1990), the central government designated automobile manufacturing as a pillar industry and called for actively utilizing FDI and technology licensing to develop manufacturing capabilities. However, the government did not establish any specific guidelines on how to utilize foreign investment to stipulate technology transfer until 1994. During the intervening years, multiple JVs were formed where foreign automakers offered know-how and product lines as equity while domestic partners provided manufacturing facilities and labor.

The manufacturing activities in the early JVs almost exclusively consisted of assembling imported "knockdown kits", packages of every single part and component for the vehicle. Foreign automakers made profits from selling knockdown kits on outdated models by avoiding the high import tariff on

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

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

vehicles at that time.[5] While foreign automakers in JVs were expected to get the technology into production, the defacto policy of the 1980s regarding JVs had no explicit provisions or mechanisms in place for technology transfer. In addition, there was very limited competition during that period, which further reduced the incentive for foreign automakers to bring in advanced technology. As a result, technology transfer was minimal in the early years of policy experimentation, a deficiency that the *quid pro quo* policy was designed to correct.

Quid Pro Quo The JV policy (or *quid pro quo*) as a national policy that we know today was formally established in the first-ever industrial policy for the automotive industry in 1994, when the State Council (China's Central Government) issued the "Automotive Industry Development Policy." This 1994 policy reaffirmed the important role that foreign investment could play while laying out specific guidelines for JV formation and industry development in general. Three stipulations were most relevant for the JVs. The first one was on ownership, which capped the foreign share at 50%. The second required the establishment of internal research centers for product development as a mechanism for technology transfer and training local talents. The third one incentivized the usage of local parts and components while explicitly prohibiting the assembly of complete or semi-complete knockdown kits.

Policy Rationales of *Quid Pro Quo* To better understand the rationales behind the design of *quid pro quo*, it is critical to recognize that there is significant misalignment among the objectives of the three key players involved: the Chinese government, Chinese automakers, and foreign automakers. The overarching goal of the Chinese government, as explicitly stated in the 1994 "Automotive Industry Development Policy," was to develop the domestic automotive industry into a pillar of the national economy, capable of generating spillover benefits to related industries and competing in the international market. On the other hand, Chinese automakers (all state-owned enterprises (SOEs), with the exception of JVs) focused on tangible short-term goals such as achieving production and sales targets rather than developing domestic technical capabilities.[6] As for foreign automakers, their interests were gaining a foothold in the high-potential growth market and generating profits without compromising their technological competitiveness.

The early experiences with JVs before 1994 demonstrated to the Chinese government that although JVs could facilitate production, they did not inherently ensure technology transfer from foreign to domestic automakers. The guidelines under *quid pro quo* as stated in "Automotive Industry Development Policy" reflected the lessons learned from the early experience. They were deliberately chosen to achieve the long-term national goal of building a strong domestic automotive industry while recognizing the different incentives of domestic and foreign automakers.[7] For example, the prohibition of knockdown

[5] The import tariff was 220% for passenger vehicles with an engine size of 3L and above and 180% for smaller engines before 1994. The tariff was reduced to 150% and 110% for the two categories in 1994. Additional cuts were made in 1997 and 2001 and finally reached 25% in 2006 as part of the condition of China's WTO accession. Auto parts faced lower tariffs.

[6] SOEs suffered from many agency problems and challenges, had weak performances and were subject to a series of reforms during that time (Cauley and Sander, 1992; Groves et al., 1994; Jefferson, 1998; Lin, Cai, and Li, 1998).

[7] This is in the spirit of the argument laid out in Naughton (1995) that the series of reforms undertaken by the Chinese

kits assembly was a direct response to the dissatisfying performances of the first two JVs. In addition, the requirements for research centers and product development established the mechanisms through which domestic automakers could acquire technological know-how. The stipulations on local parts and components promoted the development of the auto parts sector.

As with the other requirements, the choice of 50% as the cap on foreign partners' equity shares was likely driven by the recognition of the misalignment in incentives as well as the risk calculations by foreign automakers discussed above. On the one hand, allowing Chinese automakers to be the equal partner in the JVs afforded them firm control over key decisions such as product development and input sourcing, which are important for learning the 'know-how.' On the other hand, a lower than 50% equity share for foreign partners in the presence of explicit technology-transfer requirements might exacerbate the hold-up problem, diminish foreign firms' incentive to bring recent products and technology, or deter their investment in China altogether.[8] Consistent with these discussions, in the first four JVs formed before the 1994 policy (AMC-BAIC, VW-SAIC, VW-FAW, and Citroen-Dongfeng), the foreign ownership share was 31%, 50%, 40%, and 30%, respectively. After the policy, the foreign ownership share was almost always at 50%. The increase in foreign share over time could be partly attributed to foreign automakers gaining more confidence in China's reform policy and the reduced expropriation risk. At the same time, the rapid industry growth suggested greater upside potential for investing in China.

A.2 Additional Data Summaries

To examine worker mobility, we collect data on the employment history for all past and current employees in the Chinese auto industry who are registered on LinkedIn (China). The data contain 52,898 LinkedIn users who have worked in JVs and domestic firms. We identify 4,099 users who moved at least once from one automobile company to another. Of these, 617 moved from JVs to domestic firms. For each job switch, we compile information on the firm name and location before and after the switch.

Data on the auto parts suppliers is compiled from MarkLines's Who Supplies Whom database. MarkLines collects supplier information in a number of ways. Some information is directly sourced from supplier companies or downstream assembly firms. Some is obtained from vehicle teardowns, where supplier information is retrieved from the label or stamp on vehicle parts. Press releases and news articles are another important data source. MarkLines started collecting data in 2008, but most of the supplier information is available only for models produced after 2012. Our final sample covers 1,378 distinct part suppliers, 271 vehicle parts under 31 part categories, and 459 vehicle models. Examples of part categories include the ventilation system, the engine's lubrication system, interior accessories, and exterior accessories. A part category contains multiple parts. For example, the lubrication system of the engine includes a sump, oil galleries, an oil pump, and a filter.

Each auto parts company supplies on average 2.8 parts for 11 vehicle models, and there are a small

---

government since 1978 were perforce and reactive under the broad consensus on the importance of opening markets.

[8] While the 50% cap represents an intuitive middle ground amidst complex competing forces, whether it was optimal or not is an empirical question that is beyond the scope of this study.

number of large suppliers that cover many parts and models. For an average model, we have supplier information on 39 vehicle parts.

B Details of Additional Empirical Analyses

B.1 Roles of Entry and Exit

Entry-exit decomposition To understand the role of entry and exit in quality upgrading, we follow Foster, Haltiwanger, and Syverson (2008) and decompose the observed quality improvement into components attributable to continuing models, the entry of new models, and the exit of old models. We describe our decomposition exercise below.

Let $\mathcal{N}_t$ denote the set of all models in year t. Let $\mathcal{I}_t$ denote the set of models that continued from year $t-1$ to t; $\mathcal{E}_t$ denote the set of new models in year t; and $\mathcal{X}_{t-1}$ denote the set of models that are no longer present in year t. Using the corresponding capital letters N_t, I_t, E_t, X_{t-1} to denote the number of models in each set, we have $N_t = I_t + E_t$ and $N_{t-1} = I_t + X_{t-1}$.

$$
\begin{aligned}
\Delta\overline{IQS}_t &= \frac{\sum_{i\in\mathcal{N}_t} IQS_{it}}{N_t} - \frac{\sum_{i\in\mathcal{N}_{t-1}} IQS_{i,t-1}}{N_{t-1}} \\
&= \frac{\sum_{i\in\mathcal{I}_t} IQS_{it} + \sum_{i\in\mathcal{E}_t} IQS_{it}}{N_t} - \frac{\sum_{i\in\mathcal{I}_t} IQS_{i,t-1} + \sum_{i\in\mathcal{X}_{t-1}} IQS_{i,t-1}}{N_{t-1}}
\end{aligned}
$$

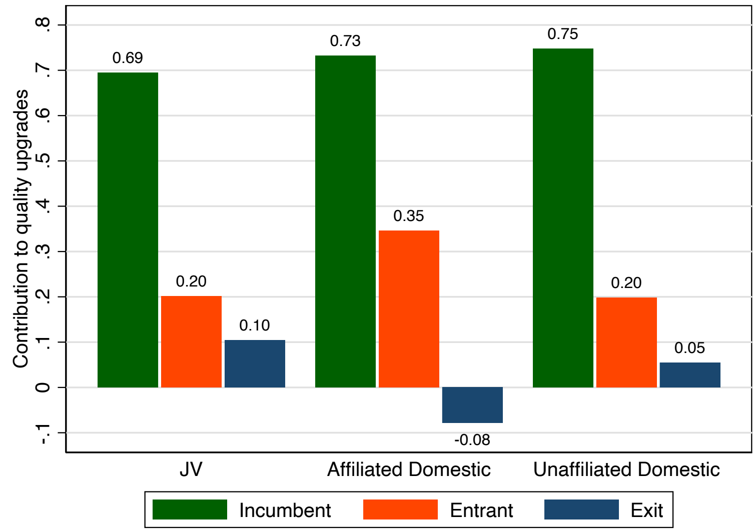
Rearranging terms, we have:

$$
\begin{aligned}
\Delta\overline{IQS}_t &= \underbrace{\frac{N_{t-1}\sum_{i\in\mathcal{I}_t}(IQS_{i,t} - IQS_{i,t-1})}{N_{t-1}\times N_t}}_{Incumbent} + \underbrace{\frac{N_{t-1}\sum_{i\in\mathcal{E}_t} IQS_{i,t} - E_t\sum_{i\in\mathcal{N}_{t-1}} IQS_{i,t-1}}{N_{t-1}\times N_t}}_{Entrant} \\
&+ \underbrace{\frac{X_{t-1}\sum_{i\in\mathcal{N}_{t-1}} IQS_{i,t-1} - N_{t-1}\sum_{i\in\mathcal{X}_{t-1}} IQS_{i,t-1}}{N_{t-1}\times N_t}}_{Exit}
\end{aligned}
$$

The first term measures quality improvement within the set of continuing models. The second term measures the quality gap between the entrants in year t and models in year $t-1$. The last term captures the extent to which exiting models had below-average quality. We conduct the decomposition exercise separately for each firm type and year and then calculate the fraction of quality changes attributable to incumbents, entrants, and exits.

Figure B.1 depicts the decomposition separately by firm type: JV models, models by affiliated domestic firms, and models by nonaffiliated domestic firms. Quality improvement among continuing models is the primary driver of quality upgrades across all three firm types. New models account for a larger fraction of quality upgrades for affiliated domestic models (35%) than nonaffiliated domestic models (20%) or JV models (20%). These new models by affiliated domestic firms potentially embody advanced technological know-how acquired from JVs. Interestingly, exiting models are not necessarily inferior in quality (as indicated by the negative bar for affiliated domestic firms), but exits contribute the least to overall quality improvements across all types.

Figure B.1: Contribution of Entering, Exiting, and Continuing Models to Quality Upgrades



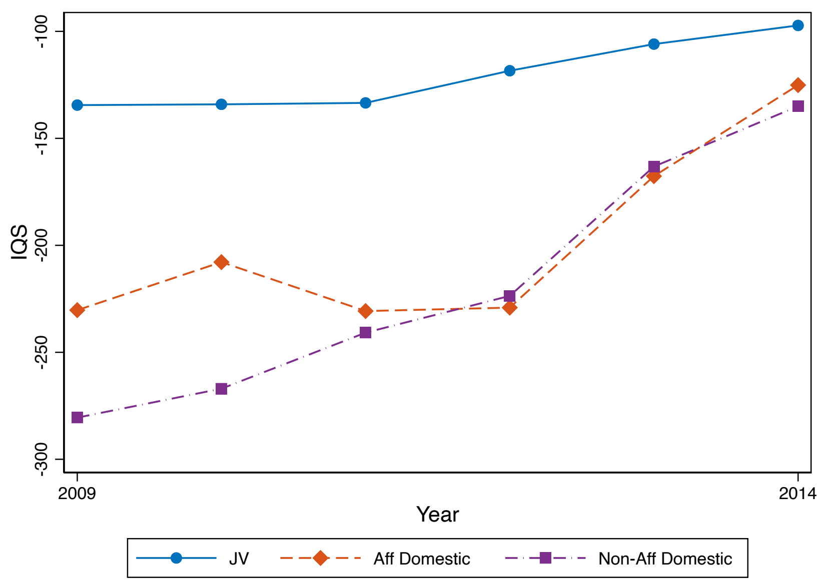
Notes: We decompose the observed quality improvements attributable to continuing models, the entry of new models, and the exit of old models. Quality is measured using total IQS scores. We implement the decomposition for each firm type and year, and then take average for each firm type, weighted by the total number of models by that firm type in each year.

Knowledge Spillovers to New and Continuing Models We analyze knowledge spillovers to new and continuing models. One informative exercise is to repeat our analyses on a perfectly balanced sample covering all 14 years of our data. Unfortunately, this is not feasible due to frequent model turnover in our dataset – only 37% of JV models and 17% of domestic models last for more than six years in our sample. Given this constraint, we analyze various sub-samples of models that have been present for a significant duration during the sample period and assess the robustness of our findings. We use the following four sample definitions:

1. Models present for all 6 years between 2009 and 2014 (a balanced sample).
2. Models present for all 5 years between 2010 and 2014 (a balanced sample).
3. Models present for at least 6 years in our sample.
4. Models present for at least 5 years in our sample.

Figure B.2 shows similar time trends of quality improvement in a balanced sample of models that are present for all 6 years between 2009 and 2014. In Table E.5, we estimate our preferred specification using the four sub-samples described above. The estimated effects are somewhat larger than those obtained in the full sample, ranging from 0.18 to 0.21 across columns. The estimates are statistically significant at the 5% level across all specifications, except in Column (1) where the p-value for the triple-interaction term is 0.101. These results are consistent with our finding that quality improvement was primarily driven by quality upgrading in continuing models.

Figure B.2: IQS Trend of Models Offered throughout 2009 - 2014



Notes: The sample consists of models sold for all six years between 2009 and 2014. The vertical axis reports the IQS score, which is the total number of problems experienced per 100 vehicles during the first 90 days of ownership across nine performance dimensions. We show the average IQS score across all models of each ownership type. We multiply the IQS score with -1 so that higher values along the y-axis indicate higher quality (for example, -100 denotes a better quality than -300).

B.2 Measurement Errors

The J.D. Power quality scores may be measured with errors. We implement an instrumental variable (IV) strategy to gauge the extent of the potential attenuation bias from measurement errors.

To do that, we leverage quality measures constructed from two different sub-samples of the underlying consumer surveys. Recall that to construct the quality measures for each car model, JD Power recruits subjects who have purchased a vehicle in the past year from over 50 cities in China and surveys their user experience. In 2014, the total number of survey respondents was 18,884, with around 110 car owners per model. While we do not have access to the micro-level consumer survey data, JD Power divides the underlying survey sample between 2001 and 2014 into two halves and provides us with quality measures constructed from each half of the sample (following the same procedure for constructing the various subscores in the full sample). This allows us to use one set of JV quality measures as the main regressor and the other set as the instrument. This IV strategy corrects the attenuation bias if the measurement errors in the two half samples are uncorrelated.

The results from four regressions are reported in Table E.7. Columns (1) and (2) use the unrestricted sample while columns (3) and (4) restrict the sample to model years with at least 50 respondents for the half samples. The sample restriction ensures that the average sample size (the number of car owners surveyed per vehicle model) in the half samples is close to the average sample size in the original full sample. Quality measures based on the two half samples are highly positively correlated, with the first-stage F-statistic being 353 and 426 for the two specifications, respectively. While the IV estimates are larger than the OLS estimates in both specifications, the Hausman test fails to detect statistically significant differences between OLS and IV estimates in either specification. The lack of both statistical significance and economic significance alleviates the concern of attenuation bias from potential measurement errors.

B.3 Permutation Analysis

We implement a permutation analysis in which we generate placebo spillover estimates based on randomly generated ownership affiliations. We randomly assign JV – domestic affiliations at four different levels: model–year, model, firm–segment, and the firm level. This allows us to assess the statistical significance of our results at different levels of clustering. We construct 300 random placebo samples of random affiliations for each level of permutation, keeping the fraction of affiliated pairs fixed in each sample.

Our analysis closely follows the approach outlined in Chetty, Looney, and Kroft (2009). The main object of interest is δ, the sum of *SameGroup*, *SameSegment*, and *SameGroup* $\times$ *SameSegment* coefficients. Our baseline estimate δ^* is 0.098, as reported in Column (2) of Table 3 in the manuscript. We plot the distribution of the estimated δ across the placebo samples and mark where our estimate $\delta^* = 0.098$ stands in these distributions. If most of the placebo samples deliver much smaller estimates of knowledge spillovers or no spillover at all, then the estimates reported in Table 3 are significant and unlikely to be driven by spurious correlations.

Following Chetty, Looney, and Kroft (2009), we define $G(\delta)$ as one minus the empirical cumulative distribution function of these placebo estimates. The statistic $G(\delta^*)$ provides a p-value for the null hypothesis that $\delta = 0$. Figure E.6 reports the result. The $G(\delta^*)$ statistic is 0 when we randomly assign the "JV-domestic affiliations" at the model-year level (the top-left panel). The $G(\delta^*)$ statistic is 0.03 and 0.04 when the affiliation is randomly assigned at the model level and firm-segment level (the top-right and bottom-left panel), respectively. As the number of firms is somewhat limited, there is a high overlap between the randomly assigned affiliations and the actual affiliations when we conduct the permutation test at the firm level (the bottom-right panel). The $G(\delta^*)$ statistic is 0.08 even for this most demanding test. These results confirm our main finding that knowledge spillovers are stronger among JVs and affiliated domestic firms compared to random pairs of firms.

B.4 Event Study

A standard event study would be ideal to examine how knowledge spillovers evolve over time. Unfortunately, a standard event study with both pre-and post-JV periods is infeasible in our setting due to the complete absence of domestic production of passenger vehicles before JV formations. Furthermore, very few domestic firms introduced models immediately after JV formation. For example, there is only one affiliated domestic model within the first two years of JV formation in the entire sample. Consequently, if we were to attempt a pre- vs. post-JV event study, we would have no pre-periods, and many of the coefficients, especially the most informative ones in the initial years post-JV formation, would hinge on a very small number of observations.

In light of this, we define the baseline year as the first year when an affiliated domestic firm first introduced its own model. In other words, the baseline year is defined as the first year that a pair of affiliated domestic and JV models appear in the data (note that this could be several years after the JV has been formed). Figure E.7 below shows the results, where the running time variable on the x-axis represents the current year minus the baseline year. We control for the interactions between JVScore and dummy variables for each affiliated firm-pair to account for baseline correlation in quality strength when the domestic firm starts introducing its own models. The coefficients illustrate the intensity of knowledge spillovers (the correlation in relative quality strength) within an affiliation as time progresses. The findings are broadly consistent with Table 4, indicating that knowledge spillovers strengthen over time, but it can take years for knowledge spillovers to occur.

C Consumer Survey on Brand Association

We leverage two additional consumer surveys to gauge consumers' awareness of JV partnerships in China's automobile industry. The purpose is to examine whether the observed knowledge spillovers were driven by brand image association, either through consumer perception or firms' strategic investment in specific quality dimensions.

The first survey was conducted offline by a Chinese market research company and covers 200 visitors at car dealers in a large Northern city. The city has no local automakers, which helps avoid potential biases arising from better recognition of local JVs. The survey respondents are either potential buyers or existing owners of vehicles. The demographic makeup of the survey respondents closely resembles that of the nationally representative survey of vehicle owners described in section 2.3. 69% of the respondents are male. 21% are 30 years old or below, 31% in the 30s, 28% in the 40s, and 20% above 50 years old. 18% are high-school graduates, and 36% have a Bachelor's degree or above. 80% own or used to own a car.

In addition to the offline survey, an online survey was conducted in November 2023 covering 10 cities in China. The online survey was conducted by a large online survey company in China (Wenjuanxing). The sample includes 200 respondents who either owned a car or expressed an intent to purchase a car in the near future. Subjects were from the top ten cities in terms of total automobile sales between 2009 and 2015, with 20 subjects from each city. The inflation-adjusted income distribution mimics that from the household vehicle ownership surveys between 2009 and 2015.

For both the offline and online surveys, the questionnaire lists 132 potential pairs of domestic and foreign firms (in the matrix form as shown in Figure C.1 below). Sixteen of them are affiliated pairs: Mercedez Benz-BAIC, Hyundai-BAIC, PSA-Changan, Ford-Changan, Suzuki-Changan, Toyota-FAW, VW-FAW, PSA-Dongfeng, Honda-Dongfeng, Nissan-Dongfeng, Honda-GAC, Toyota-GAC, BMW-Brilliance, Jaguar-Chery, GM-SAIC, VW-SAIC. Respondents were asked to check JVs that they recognize. The rows and columns are randomized among the respondents to account for potential cognitive biases, e.g., consumers failing to recognize JVs that appear later in the table because they get tired.

Figure C.2 shows the result. We find a large positive correlation of 0.87 in the brand association measure between the two surveys, which is reassuring. We observe significant variations in brand association across different JVs: for example, 74% of consumers recognized the BMW-Brilliance affiliation, compared to only 7% who recognized PSA-Changan.

Figure C.1: Survey Questionnaire

1. Gender: Male Female

2.Age: <30, 30-40, 40-50 >50

3. Education: High school or below, Junior college or diploma, Bachelor or above

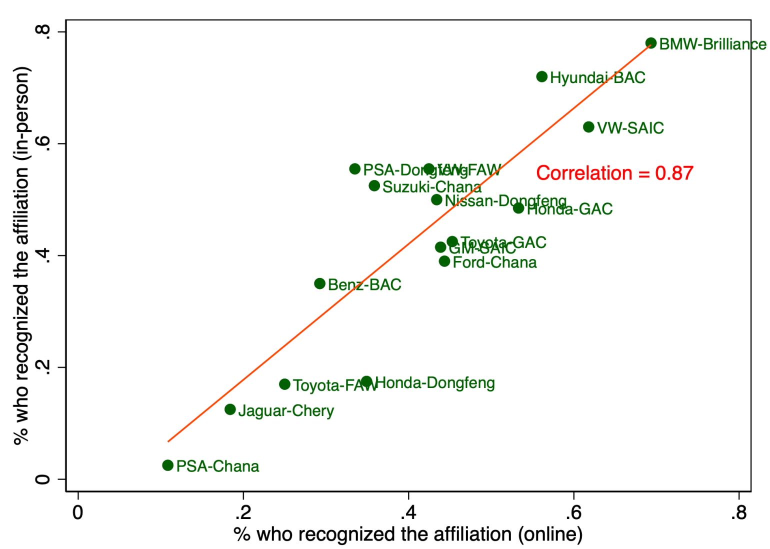
4. Do you or your family own or used to own a car: Yes No

If "yes," please list all car models you have owned (now and past):

5. **In the table below, each row is a domestic carmaker, and each column is a foreign carmaker. Please check any joint ventures that you recognize. For example, if domestic carmaker X is a joint venture partner with foreign carmaker Y, please check the cell under row X and column Y. If you think X has multiple joint venture partners, please check all the corresponding cells. If you believe X does not have any joint venture partner, please leave the row blank.**

	BMW	Benz	PSA	Honda	VW	Toyota	Jaguar	Ford	Suzuki	Nissan	GM	Hyundai
Beijing Auto												
BYD												
Changan Auto												
Great Wall												
First Auto Works												
Dongfeng Auto												
Guangzhou Auto												
Brilliance												
Geely												
Chery												
Shanghai Auto												

Figure C.2: Correlation in Brand Recognition between the Two Surveys



Notes: This figure shows the fraction of consumers who correctively recognized the JV affiliation between the foreign and domestic firms in the two consumer surveys. We implemented one survey online and the other survey in person in Shijiazhuang, Hebei province. The sample size of each survey is 200.

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

We apply Equation D.1 to quantify the impact of *quid pro duo* on domestic quality upgrades since 2001. We use the total IQS score as the quality measure by aggregating Equation D.1 across 9 dimensions of IQS, and assume that knowledge spillovers are proportional to the average JV quality (179 defects) and the initial quality of affiliated domestic models (498 defects). Knowledge spillovers due to *quid pro duo* improved the IQS score of affiliated domestic firms by around 31 defects ($(179-498)\times 0.098 = -31$). This accounts for 8.3% of the total reduction of 375 defects over the sample period from 2001 to 2014.

One may be concerned that the initial quality of affiliate domestic firms are noisily measured due to the small sample size in 2001. If we use the average IQS during 2001-2023 as the initial quality measure, we also find that knowledge spillovers due to *quid pro duo* contribute 8.3% of quality improvement by affiliated domestic firms ($\frac{(179-485)*0.098}{-362} = 8.3\%$).

To illustrate conceptually how knowledge spillovers lead to shared comparative advantages between affiliated JV and domestic models, we write a stylized model. We take the linear specification in Equation (2) literally and assume that the size of spillovers between affiliated JV-domestic pairs is proportional to the quality gap between the two. With some additional assumptions, this model allows us to quantify the impact of *quid pro quo* on domestic quality upgrades.

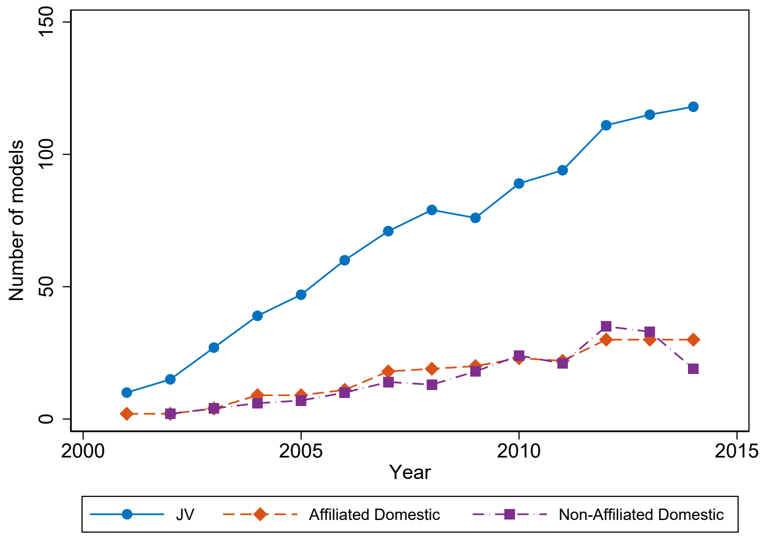
Consider one representative pair of follower and leader. Let q_k denote the observed quality of the follower in quality dimension k. Let $\delta_k = \bar{\delta} + \varepsilon_k$ denote the baseline quality of the follower in dimension k in the absence of knowledge spillovers. It consists of a component $\bar{\delta}$ common to all quality dimensions and a dimension-specific component ε_k. Let Q_k denote the observed quality of the leader in quality dimension k. It can be similarly decomposed into $\bar{Q}$ and μ_k, where μ_k measures dimension-specific comparative (dis)advantage. Let ρ denote the intensity of spillovers. We write:

$$
\begin{aligned}
q_k &= \delta_k + \rho(Q_k - \delta_k) && \text{(D.1)} \\
&= \underbrace{(1-\rho)\bar{\delta} + \rho\bar{Q}}_{\text{Follower's average quality}} + \rho\mu_k + (1-\rho)\varepsilon_k && \text{(D.2)}
\end{aligned}
$$

Equation D.2 maps to our two-step empirical framework. In the first step, we partial out the average quality (i.e., model-year fixed effects) to derive dimension-specific relative strengths. The leader's relative strength in dimension k is μ_k, while the follower's relative strength is $\xi_k = \rho\mu_k + (1-\rho)\varepsilon_k$. The coefficient ρ captures the transmission of relative strengths from the leader to the follower as the result of knowledge spillovers. The follower's intrinsic relative strength in the absence of spillovers, ε_k, shows up as a noise in the estimation. The identification assumption is that the follower's intrinsic relative strength ε_k is independent from the leader's relative strength μ_k. We examine and rule out potential threats to this assumption, such as endogenous JV formation, overlapping consumer base, brand association and direct technology transfer in Section 4.3.

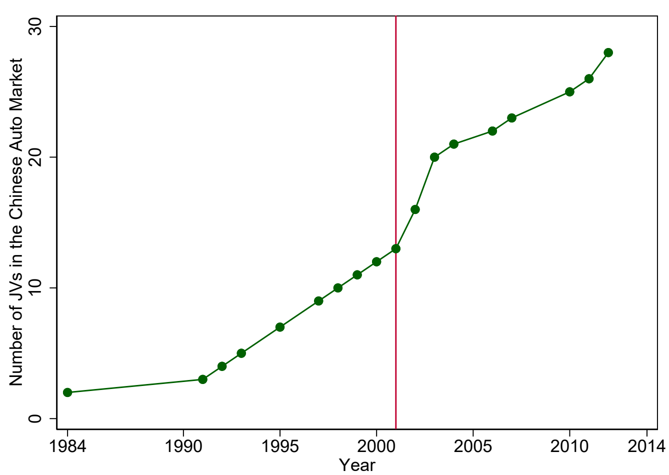
E Figures and Tables

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



Notes: Thig figure shows the the number models of each firm type covered by the J.D. Power surveys in each year. Affiliated domestic firms are the domestic automakers that have joint ventures with foreign automakers. They are all SOEs. The number of models from these automakers indicates the indigenous brands, i.e., brands produced solely by the domestic automakers. Nonaffiliated domestic automakers are those automakers that do not have joint ventures.

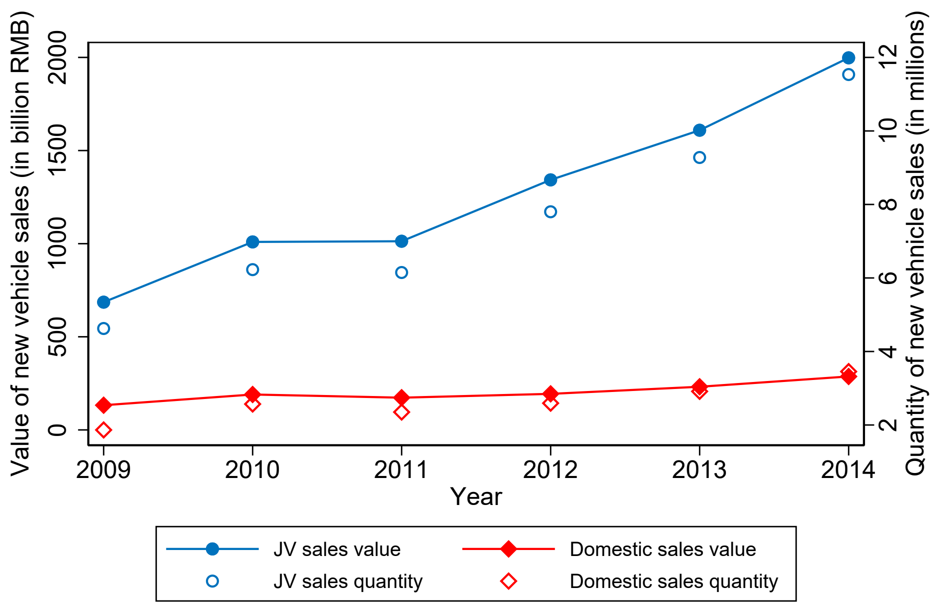
Figure E.2: Entry of Joint Ventures



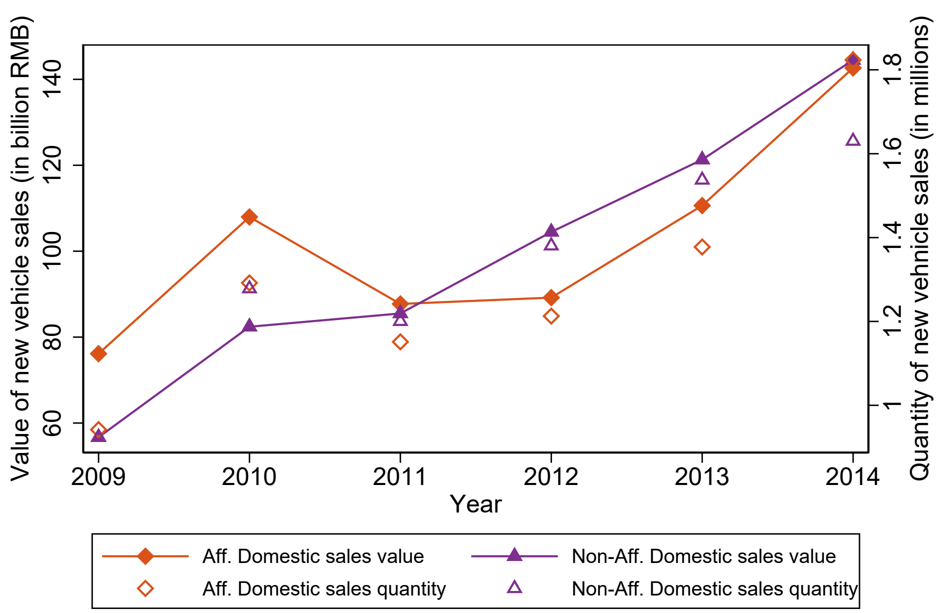
Notes: The figure plots the number of JVs in the Chinese auto market over time. Significant entries include: (1) 1984-1994: VW-Shanghai, VW-FAW, PSA-Dongfeng, Suzuki-Changan; (2) 1994-2000: GM-Shanghai, Honda-Guangzhou, Toyota-FAW, Suzuki-Changhe; (3) post 2000: Ford-Changan, Nissan-Dongfeng, Hyundai-Beijing,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

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

Panel A. Performance of JVs and Domestic automakers



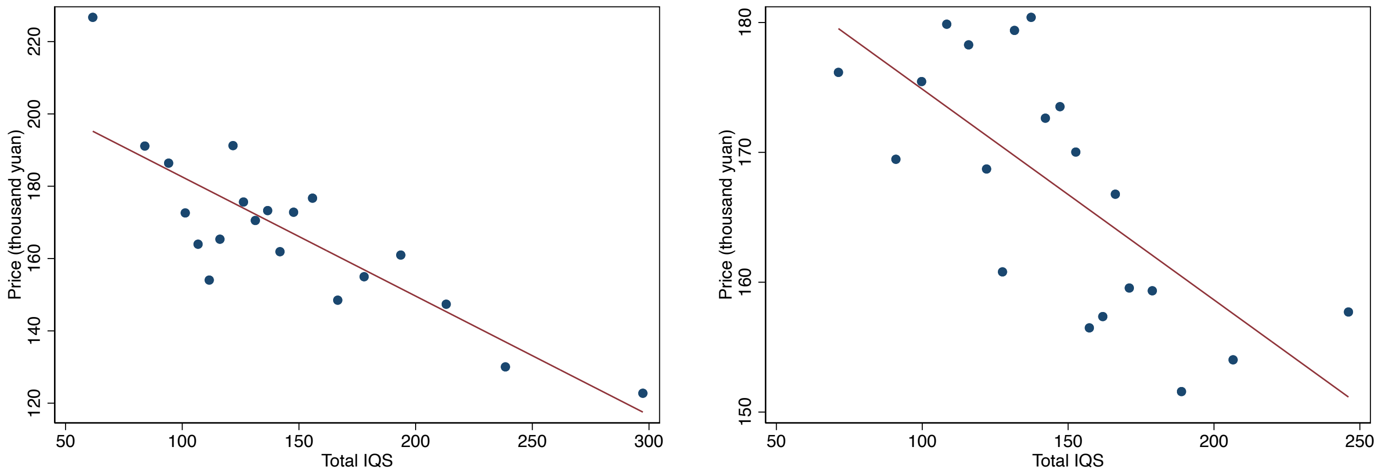
Panel B. Performance among Domestic automakers



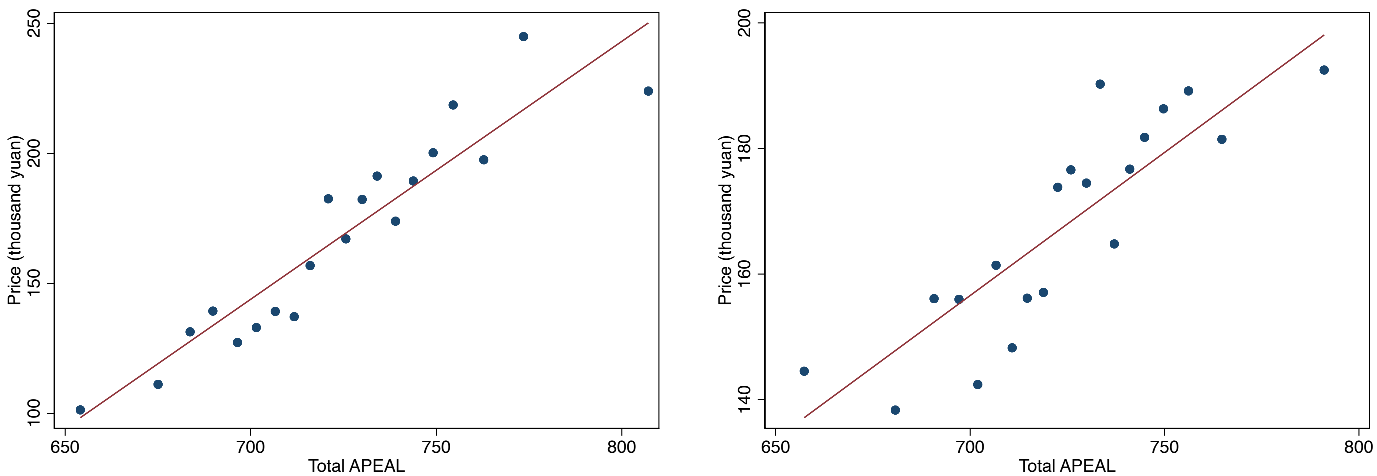
Notes: Sales value and quantity are calculated using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year. It does not include imported models, which account for around 3% of total sales.

Figure E.4: Correlation between Vehicle Price and IQS Scores

Panel A. Vehicle Price vs. IQS

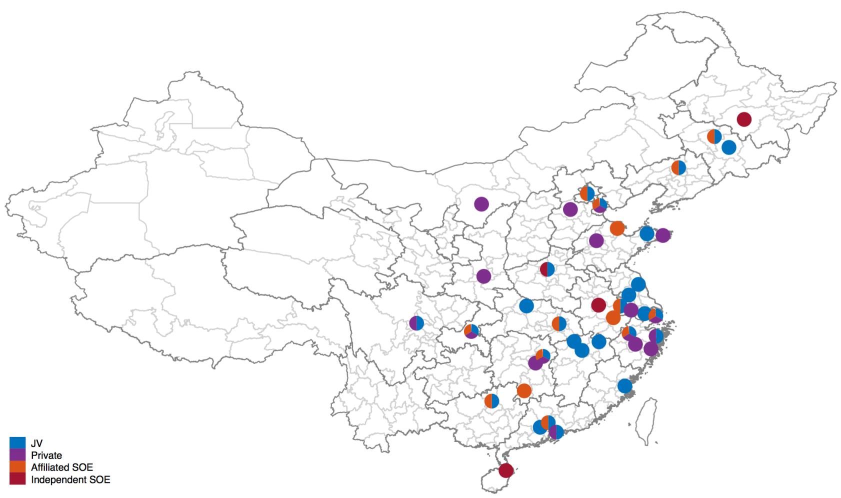


Panel B. Vehicle Price vs. APEAL



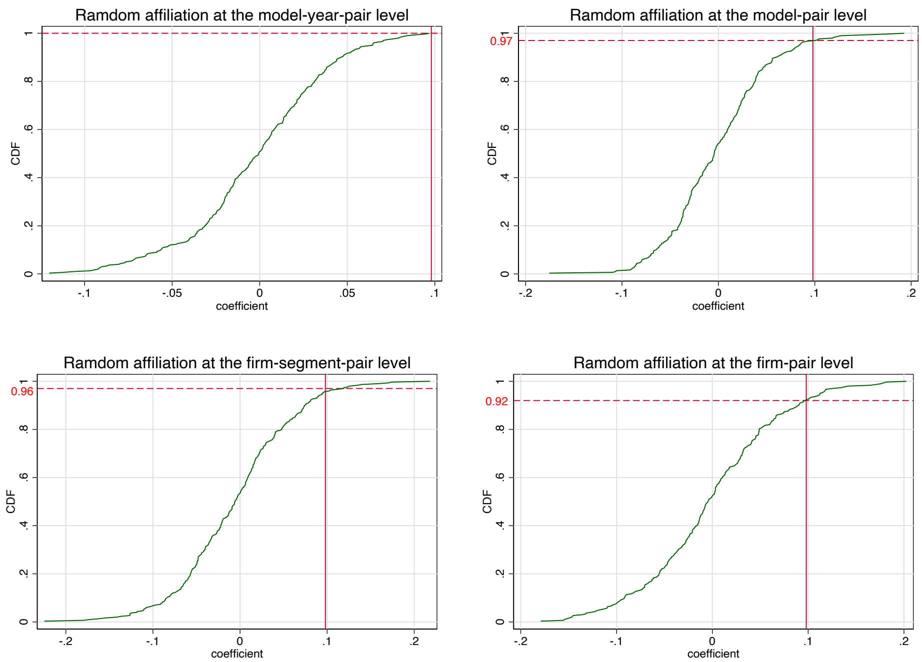
Notes: The figures are binned scatter plots between price and the IQS score (Panel A) and between price and the APEAL score (Panel B) based on data from 2009 to 2014. The price data are only available only since 2009. The left figures control for vehicle size and horsepower/weight. The right figures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

Figure E.5: Geographical Distribution of Vehicle Production Plants in China



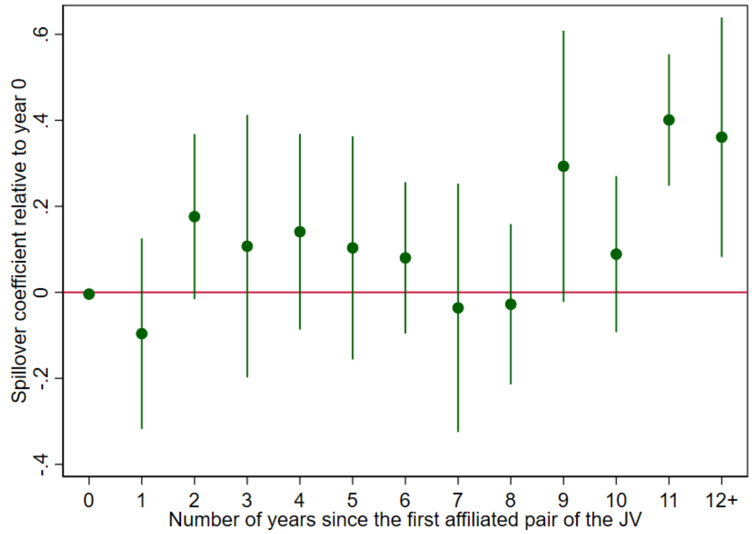
Notes: This figures shows a map of vehicle production sites in China. Each circle represents a city. Colors of the circle indicate the ownership composition of the production plants located in a given city.

Figure E.6: Permutation (Placebo) Analyses



Notes: This figure shows the results of four permutation analyses. We randomly assign the "JV-domestic affiliations" at four levels: model-year, model, firm-segment, and firm level. For each permutation analysis, we construct 300 placebo samples with random affiliations, holding fixed the fraction of affiliated pairs in each placebo sample. We plot the empirical CDF of the sum of $SameGroup$, $SameSegment$, and $SameGroup \times SameSegment$ coefficients in each permutation analysis. The red vertical lines mark our baseline estimate $\delta = 0.098$ using the actual affiliations. We mark the empirical cumulative distribution function of these placebo estimates that is evaluated at $\delta = 0.098$ on the vertical axes.

Figure E.7: Knowledge Spillovers within an Affiliated Firm Pair over Time



Notes: This figure plots the coefficients and 95% confidence intervals from the event study specification. The horizontal axis shows the number of years since the first affiliated pair of the JV showed up in the data, with year 0 as the omitted baseline. In other words, year 0 is the year when an affiliated domestic firm introduced its first indigenous model. The specification controls for the baseline spillover intensity for each pair of affiliated firms at year 0.

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

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

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

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

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

Table E.3: Relative Quality Strength Correlation between US and JV Models

	(1)	(2)	(3)
US Score	-0.002*	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
× SameForeignFirm	0.031	0.024	0.023
	(0.021)	(0.020)	(0.020)
× SameSeg		-0.004***	-0.004***
		(0.000)	(0.000)
× SameForeignFirm × SameSeg		0.059***	0.045***
		(0.014)	(0.014)
× SameName			0.115***
			(0.042)
Observations	1,866,560	1,866,560	1,866,560
Partialing out:			
Model-Year FE	✓	✓	✓
Segment-Dimension-Year FE	✓	✓	✓

Notes: The dependent variable is the quality score of a JV model. We consider all pairs of JV and US models. The unit of observation is a pair-year-quality dimension. Both leader (US) and follower (JV) scores are residualized scores after partialling out model-year and segment-dimension-year fixed effects. SameForeignFirm is a dummy variable indicating if the model pair shares the same foreign automaker (e.g., Brilliance-BMW and BMW). SameSeg indicates if the pair belongs to the same vehicle segment. Finally, SameModel indicates if the pair shares the same model name in the US and Chinese markets. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table E.4: Knowledge Spillovers: Fixed Effect Models

	(1)	(2)	(3)	(4)	(5)	(6)
JVScore	-0.003	-0.002	-0.007**	-0.006*	-0.007**	-0.008**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
× SameGroup	0.053	0.033	0.004	0.022	0.017	0.021
	(0.046)	(0.045)	(0.039)	(0.042)	(0.038)	(0.051)
× SameSeg		-0.008***	0.035**	0.022**	0.031*	0.032***
		(0.002)	(0.017)	(0.011)	(0.016)	(0.011)
× SameGroup × SameSeg		0.127**	0.116**	0.093**	0.113**	0.145**
		(0.047)	(0.056)	(0.044)	(0.052)	(0.057)
Observations	738,695	738,695	739,001	739,001	739,001	739,001
Controlling for:						
Model-year FE	✓	✓				✓
Dimension-Segment-Year FE	✓	✓				
Firm FE			✓			
Firm-year FE				✓		
Model FE					✓	
Dimension-year FE			✓	✓	✓	✓
Dimension-Segment FE			✓	✓	✓	✓

Notes: This table replicates the specifications in Table 3 using one-step estimation with fixed effects (standard OLS). The dependent variable is the quality score for domestic vehicles (followers), and 'JVScore' is the quality score for JV vehicles (leaders). All firm, model, and segment fixed effects are defined for the leader-follower pair (the domestic model and JV model pair). Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table E.5: Knowledge Spillovers Using Balanced Panels or Models with Long Duration

	(1) 2009 - 2014	(2) 2010 - 2014	(3) At least 6 yrs between 2001-2014	(4) At least 5 yrs between 2001-2014
JVScore	-0.001	-0.000	0.000	-0.001
	(0.001)	(0.002)	(0.008)	(0.003)
× SameGroup	0.008	0.004	-0.010	0.010
	(0.006)	(0.016)	(0.019)	(0.019)
× SameSeg	-0.013	-0.017**	-0.008	-0.012***
	(0.007)	(0.008)	(0.008)	(0.004)
× SameSegSameGroup	0.184	0.212**	0.185**	0.192**
	(0.106)	(0.092)	(0.080)	(0.079)
Observations	145,370	227,490	282,906	440,046
Partialing out:				
Model-Year FE	✓	✓	✓	✓
Segment-Dimension-Year FE	✓	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We consider all pairs of models produced by JVs and domestic automakers. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after various fixed effects are partialed out. The first two columns use balanced panels of models present between 2009 and 2014 (Column (1)) or between 2010 and 2014 (Column (2)). Columns (3) and (4) use models present for at least six or five years between 2001 and 2014. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table E.6: Knowledge Spillovers by IQS and APEAL Scores

	(1) All	(2) IQS	(3) APEAL
JVScore	-0.001	-0.000	-0.001
	(0.001)	(0.000)	(0.002)
× SameGroup	0.016	0.008	0.025
	(0.010)	(0.009)	(0.018)
× SameSeg	-0.005***	-0.006***	-0.004**
	(0.001)	(0.001)	(0.002)
× SameGroup × SameSeg	0.087***	0.103***	0.072***
	(0.018)	(0.026)	(0.024)
Observations	717,500	341,073	376,427
Partialling out:			
Model-Year FE	✓	✓	✓
Dimension-Segment-Year FE	✓	✓	✓

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

Table E.7: Instrumental Variable Analysis Using Split-Samples of JD Power Surveys

	(1) OLS	(2) IV	(3) OLS	(4) IV
JVScore	-0.005**	-0.009**	-0.004**	-0.006
	(0.002)	(0.005)	(0.002)	(0.011)
× SameGroup	0.099**	0.162***	0.075**	0.100**
	(0.038)	(0.043)	(0.036)	(0.042)
Observations	131,157	131,157	98,458	98,458
Partialling out :				
Model-Year FE	✓	✓	✓	✓
Segment-Dimension-Year FE	✓	✓	✓	✓
Sample size above 50			✓	✓
Kleibergen-Paap Wald rk F-statistic		353		426

Notes: JD Power divides the underlying survey sample between 2001 and 2014 into two halves and provides us with quality measures constructed from each half of the sample. We use one set of JV quality measures as the main regressor and the other set as the instrument for this analysis. We focus on pairs of models produced by JVs and domestic automakers in the same segment, where knowledge spillovers are strongest. Columns (1) and (2) use all model-years, while Columns (3) and (4) use model years with at least 50 respondents for the half samples. Leader (JV) and follower (domestic) scores and the instrument are all residualized scores after model-year and segment-dimension-year fixed effects are partialed out. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table E.8: Knowledge Spillovers: Alternative Clustering of Standard Errors

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

Notes: This table replicates Column (2) in Table 3 (the preferred specification) under four alternative clustering of the standard errors. Columns (1) clusters the standard error two-way at domestic firm-quality dimension and JV firm - quality dimension levels. Columns (2) clusters the standard error at domestic-JV firm pair-quality dimension level. Columns (3) clusters the standard error three-way at domestic-JV firm pair-quality dimension, domestic firm-quality dimension-year, and JV firm-quality dimension-year levels. Columns (4) clusters the standard error two-way at domestic firm and JV firm levels.

Table E.9: Preferred Specification with Bootstrapped Standard Errors

	(1)	(2)	(3)
JVScore	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
× SameGroup	0.016	0.016	0.016
	(0.018)	(0.021)	(0.022)
× SameSeg	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)
× SameGroup × SameSeg	0.087**	0.087**	0.087**
	(0.040)	(0.041)	(0.038)
Observations	717,500	717,500	717,500
Bootstrap block:			
Model–year-category	✓		
FirmSeg–year-category		✓	
Firm-year-category			✓

Notes: We calculate the standard errors in Column (2) of Table 3 (the preferred specification) using bootstrap. Column (1) implements the block bootstrap at the model-year-category level. Column (2) treats a firm-segment-year-category as a block while Column (3) treats a firm-year category as a block. A category includes either all IQS scores or all APEAL scores. Standard errors are calculated over 500 bootstrap samples for each column. *** implies significance at 0.01 level, ** 0.05, * 0.1.

Table E.10: Spillovers through Ownership and Geographical Networks

	(1)	(2)
JVScore	-0.006*	
	(0.003)	
× SameGroup	0.097***	
	(0.030)	
× SameGroup × SameProv		0.114**
		(0.047)
× SameGroup × DiffProv		0.080**
		(0.030)
× DiffGroup × SameProv		0.037
		(0.069)
× DiffGroup × DiffProv		-0.006**
		(0.003)
Observations	138,540	138,540
Partialling out:		
Model-year FE	✓	✓
Dimension-Segment-Year FE	✓	✓

Notes: The dependent variable is the quality score of a domestic model. The sample consists of domestic–JV pairs in the same vehicle segment where spillovers are concentrated as shown in Table 3. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after model-year and dimension-segment-year fixed effects are partialed out. Interaction terms are dummy variables indicating whether the two models belong to the same affiliated group of automakers (SameGroup) or are located in the same province (SameProv). Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at0.05, and * at 0.1.

Table E.11: Overlapping Consumer Base with Poisson Regressions

	(1)	(2)	(3)	(4)
SameGroup	-0.827***	-0.786***	0.032	-0.155
	(0.065)	(0.102)	(0.104)	(0.104)
SameSegment		1.808***	1.508***	1.044***
		(0.028)	(0.049)	(0.049)
SameGroup × SameSegment		-0.142	0.157	0.055
		(0.130)	(0.136)	(0.136)
SameOwnershipType			1.206***	1.033***
			(0.034)	(0.034)
SameSegment × SameOwnershipType			0.299***	0.112*
			(0.059)	(0.059)
Same firm			0.064	-0.308***
			(0.046)	(0.052)
Observations	196,225	196,225	196,225	196,225
Control for:				
Vehicle attributes				✓

Notes: the sample is constructed from the annual household vehicle ownership survey between 2009 and 2015. Each observation is a pair of models in a year. This table reports results from Poisson regressions, where the outcome is the number of times that a pair of models is listed as the top two choices by households in the survey data. Attribute controls include differences in price, car size, and engine power. SameGroup takes value 1 for a JV model and its affiliated domestic models. SameSeg takes value 1 if both models are in the same vehicle segment. SameOwnershipType takes value 1 if both models within a pair are JV models or both are domestic models. In Columns (3) and (4), the omitted group includes pairs not produced by affiliated automakers, not in the same segment, and not produced by firms of the same ownership type. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table E.12: Brand Awareness and Knowledge Spillovers

	(1)	(2)	(3)
JVScore	-0.008*	-0.008***	-0.008**
	(0.004)	(0.003)	(0.003)
× SameGroup	0.114***	0.163**	
	(0.036)	(0.079)	
× SameGroup × BrandAssociation		-0.118	
		(0.101)	
× SameGroup × BrandAssociation High			0.019
			(0.079)
× SameGroup × BrandAssociation Medium			0.251*
			(0.125)
× SameGroup × BrandAssociation Low			0.014
			(0.061)
Observations	114,798	114,798	114,798
Partialing out:			
Model-year FE	✓	✓	✓
Dimension-Segment-Year FE	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. The sample consists of domestic-JV pairs in the same vehicle segment where spillovers are concentrated. We exclude from the sample 12 small JVs not covered by our consumer surveys. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after model-year and segment-dimension-year fixed effects are partialed out. "BrandAssociation" is a standardized measure of the fraction of survey respondents who recognize the firm affiliation (e.g., Brilliance has a JV with BMW). Column (3) divides the "BrandAssociation" score into terciles. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table E.13: Cumulative Production and Knowledge Spillovers

	(1) All	(2) All	(3) All	(4) All	(5) All
JVScore	-0.006*	-0.006**	-0.006*	-0.006**	-0.006
	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)
× SameGroup	0.097***	-0.060	0.099***	-0.071*	-0.076
	(0.030)	(0.038)	(0.031)	(0.041)	(0.046)
× SameGroup × log(Cum JV production)		0.070***		0.076***	0.074***
		(0.017)		(0.019)	(0.020)
× SameGroup × log(Cum Domestic production)			0.003	-0.004	-0.006
			(0.012)	(0.012)	(0.015)
× SameGroup × Trend					0.004
					(0.013)
Observations	138,540	136,403	133,958	131,875	131,875
Partialing out:					
Model-year FE	✓	✓	✓	✓	✓
Dimension-Segment-Year FE	✓	✓	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. We focus on pairs of models produced by JVs and domestic automakers in the same segment where spillovers are concentrated. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after model-year and dimension-segment-year fixed effects are partialed out. Interaction terms are the log of cumulative production by the JV and the domestic firm up to the previous year. Variable "Trend" is defined as the current year minus 2009. A small number of observations with missing production data are dropped between Columns (2) and (5). Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.

Table E.14: Mechanism of Knowledge Spillovers: Worker Flow and Supplier Networks

	(1)	(2)	(3)	(4)
JVScore	-0.006*	-0.005	-0.006***	-0.008**
	(0.003)	(0.004)	(0.002)	(0.003)
× SameGroup	0.097***	0.033	0.078**	0.046*
	(0.030)	(0.028)	(0.030)	(0.023)
× WorkerFlow		-0.001		0.008**
		(0.003)		(0.003)
× SameGroup × WorkerFlow		0.023***		0.019*
		(0.007)		(0.010)
× SupplierOverlap			0.016***	0.015***
			(0.002)	(0.002)
× SameGroup × SupplierOverlap			-0.004	-0.040
			(0.016)	(0.031)
Observations	138,540	138,540	128,354	128,354
Partialling out :				
Model-Year FE	✓	✓	✓	✓
Segment-Dimension-Year FE	✓	✓	✓	✓

Notes: The dependent variable is the quality score of a domestic model. The sample consists of domestic-JV model pairs in the same vehicle segment where spillovers are concentrated. The unit of observation is a pair-year-quality dimension. Both leader (JV) and follower (domestic) scores are residualized scores after model-year and segment-dimension-year fixed effects are partialed out. SameGroup equals 1 if the two models belong to a pair of affiliated automakers. WorkerFlow is a standardized measure of the number of workers who moved from a JV to a domestic automaker. SupplierOverlap is defined as the number of common suppliers divided by the number of distinct suppliers reported by the pair (the smaller number of the two), standardized across all pairs of models. In Column (3) and (4), we drop 3% of pairs for which at least one model has fewer than five distinct suppliers. Standard errors are clustered at the follower firm-category and leader firm-category level, where a quality category includes either all IQS or all APEAL scores. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.