

Supplemental Appendix

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

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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

¹Source: <https://media.gm.com/media/cn/zh/gm/news.detail.html/content/Pages/news/cn/zh/2011/Aug/0802.html>.

²However, 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.

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 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

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

⁴See <http://auto.sohu.com/20110118/n278942357.shtml>.

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 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

⁵The import tariff was 220% for passenger vehicles with an engine size of 3L and above and 180% for smaller engines before 1994. The tariffs were reduced to 150% and 110% respectively 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.

⁶SOEs 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).

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 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 misaligned 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.

⁷This is in the spirit of the argument laid out in [Naughton \(1995\)](#) that the series of reforms undertaken by the Chinese government since 1978 were perforce and reactive under the broad consensus on the importance of opening markets.

⁸While 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.

Each auto parts company supplies on average 2.8 parts for 11 vehicle models, and there are a small number of large suppliers that cover many parts and models. For an average model, we have supplier information on 39 vehicle parts.

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:

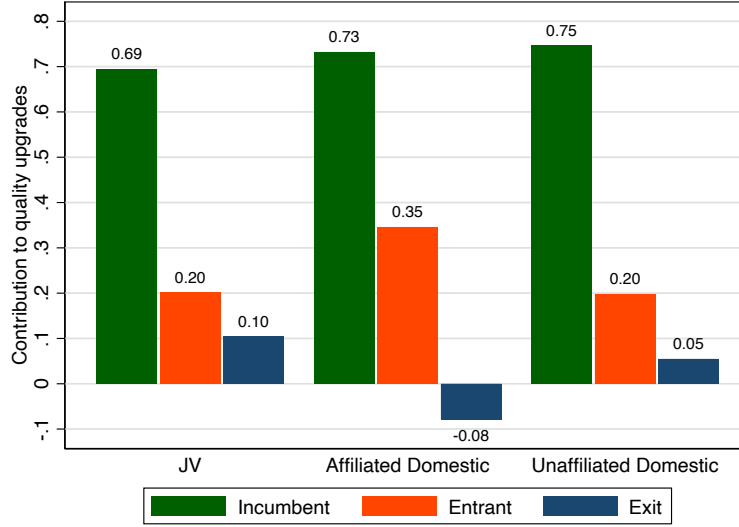
$$\begin{aligned}\Delta \overline{IQS}_t &= \underbrace{\frac{N_{t-1} \sum_{i \in \mathcal{I}_t} (IQS_{i,t} - IQS_{i,t-1})}{N_{t-1} \times N_t}}_{Incumbent} + \underbrace{\frac{N_{t-1} \sum_{i \in \mathcal{E}_t} IQS_{i,t} - E_t \sum_{i \in \mathcal{N}_{t-1}} IQS_{i,t-1}}{N_{t-1} \times N_t}}_{Entrant}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

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 upgrading across all three firm types. New models account for a larger fraction of quality upgrading 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 Upgrading



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.

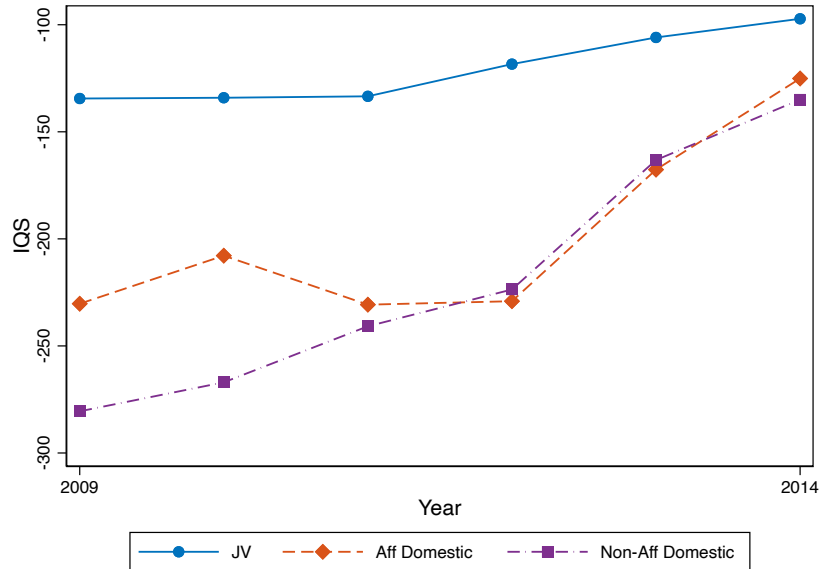
Knowledge Spillovers to New and Continuing Models We analyze knowledge spillovers to new and continuing models. One informative exercise is to repeat our analyses on a perfectly balanced sample covering all 14 years of our data. Unfortunately, this is not feasible due to frequent model turnover in our 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 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 firm. 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.

B.5 Placebo Test for Endogenous Formation

We conduct a placebo test for endogenous JV formation based on the overlap in foreign-JV partnerships. A domestic automaker may partner with multiple foreign automakers, leading to an overlap in foreign partners among different JVs. For example, as shown in Figure 1, VW forms two JVs, one with SAIC (i.e., Shanghai Auto), and the other with FAW (i.e., First Auto Works). In the meantime, FAW also forms another JV with Toyota (Toyota-FAW) but SAIC does not. Therefore, a model from SAIC (follower) and a model from Toyota-FAW (leader) can be considered to be a placebo affiliated pair in the placebo analysis with the following logic. Suppose similar relative quality strength between affiliated firms arises due to selection based on relative strength. VW and Toyota, which both selected FAW as a JV partner, should have similar relative strength. SAIC, which is also selected by VW, should then have similar relative strength as both VW and Toyota, even though SAIC and Toyota do not have a direct joint venture affiliation. The placebo test is then to examine whether models by SAIC and models by Toyota-FAW show correlated quality strengths. Following this strategy, we identify the placebo JV affiliations for each domestic firm:

- Shanghai Auto: Toyota - FAW, Mazda - FAW
- Dongfeng: Mitsubishi - GAC, Fiat - GAC, Ford - Changan, Suzuki - Changan, Toyota - GAC
- FAW: VW - Shanghai, Mitsubishi - GAC, Fiat - GAC, Honda - GAC
- GAC: VW - FAW, Mazda - FAW, Nissan - Dongfeng, Yueda - Kia - Dongfeng, PSA - Dongfeng; Yulon - Dongfeng
- Changan: Honda - Dongfeng, Nissan - Dongfeng, Yueda - Kia - Dongfeng; Yulong - Dongfeng

Table E.10 shows the results. Column (1) shows the effects of placebo affiliation. Column (2) jointly estimates the effects of true and placebo affiliations. We find that, if anything, the placebo pairs exhibit

a mild dissimilarity in their relative strength. This finding alleviates concerns of selection based on relative quality strength.

B.6 Feature Adoption Decisions

Similar relative strengths between affiliated JVs and domestic firms documented in our analysis could be partly driven by their choice to adopt similar features. To examine this potential mechanism, we collect data on vehicle attributes and technology features between 2004 and 2014. After consulting with industry professionals, we identify nine features regarded as recent technologies (i.e., new-tech features) during the sample period in China:

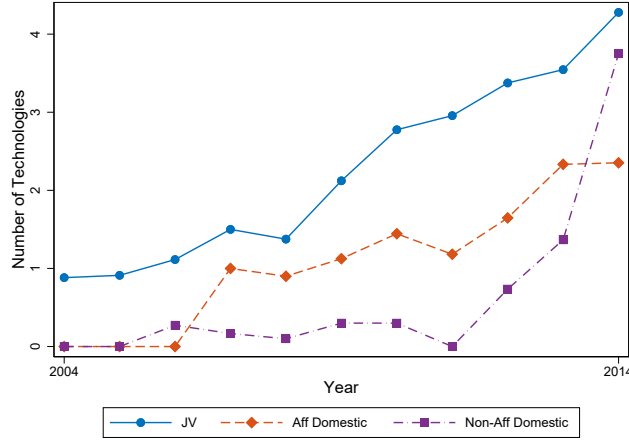
1. Dual-clutch transmission (DCT)
2. Turbocharged engine (Turbo)
3. Direct fuel injection (DFI)
4. Emergency brake assist (EBA)
5. Anti-slip regulation (ASR)
6. Electronic stability control (ESC)
7. Hill-start assist control (HAC)
8. Hill descent control (HDC)
9. Variable gear ratio steering (VGRS)

Among these, we classify DCT, Turbo, and DFI as core features because they pertain to engines and transmissions, embodying more tacit knowledge in engineering and design. The remaining six features are regarded as add-ons, which are less critical and require less tacit knowledge to incorporate. Figure B.3 depicts the time trend in the adoption of these features where the y-axis is the average number of features adopted. As expected, JV models adopt more of these features than domestic models. The adoption rate increases for all three types of firms over time. Notably, we see a spike in adoption by affiliated domestic firms around 2007 and nonaffiliated domestic firms after 2012.

We use our empirical framework to analyze whether affiliated pairs adopt similar features. Each feature is analogous to a quality dimension in our main analysis, with the outcome being an indicator for adoption. Specifically, we first recover the relative adoption propensity at the model-year-feature level, separately for JV and domestic models, by partialling out model-year fixed effects and segment-year-feature fixed effects. We then construct a sample of all pairwise combinations of JV models and domestic models from the same year. We implement the same regression specifications as in Table 3, with the dependent variable representing the adoption of a certain new-tech feature.

Table E.16 summarizes the results. Columns (1) and (2) show no evidence of knowledge spillovers in overall feature adoption decisions. Discussions with industry experts suggest that most features could be easily sourced from the market and do not require significant in-house knowledge or capability for installation. Therefore, adoption decisions mainly reflect demand-driven product positioning strategies, which we have shown to be uncorrelated between JVs and affiliated domestic firms. When we narrow the

Figure B.3: Trend in New-tech Feature Adoptions



Notes: The vertical axis reports the average number of features adopted out of the following nine high-tech features: dual-clutch transmission, Turbocharged engine, direct fuel injection, emergency brake assist, anti-slip regulation, electronic stability control, hill-start assist control, hill descent control, and variable gear ratio steering. A model is considered to have adopted a feature if any trim of the model has it.

analysis to the three core features in Columns (3) and (4), the point estimates suggest positive spillovers from JVs to affiliated SOEs in adoption decisions. The estimates are close to marginally significant at the 10% level (the p-value is 11.8% in Column (4)). These results provide suggestive evidence that knowledge spillovers may occur for features that require more tacit knowledge. We want to be cautious in interpreting these results because of the small number of features considered.

Overall, these findings shed some light on the underlying mechanisms of knowledge spillovers. They suggest that the shared relative strength between affiliated JV and domestic firms, as documented in this paper, is driven more by the transfer of tacit know-how in design and assembly processes than by the inclusion of specific product features. Furthermore, adopting new features does not necessarily result in a higher quality score, particularly if the feature is prone to defects or poorly integrated into the system.

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: Mercedes-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

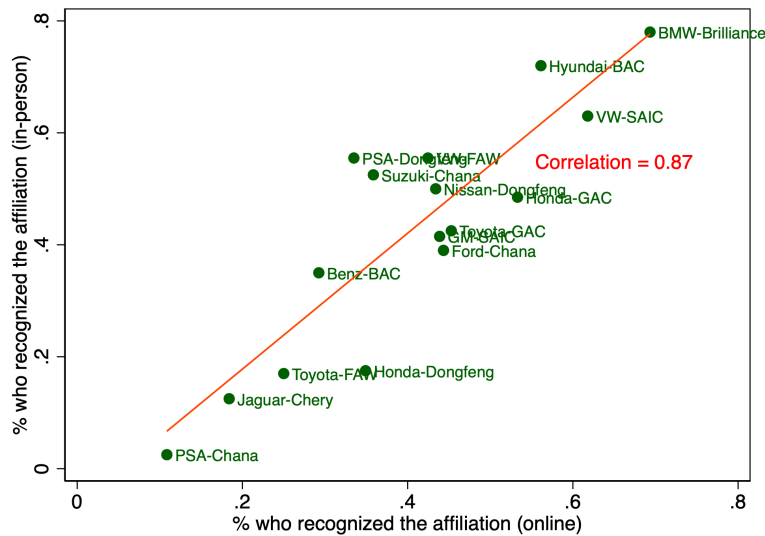
4. Do you or your family own or used to own a car: Yes No

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 correctly recognized the JV affiliation between the foreign and domestic firms in the two consumer surveys. One survey was conducted online and the other was conducted in person in Shijiazhuang, Hebei province. The sample size of each survey is 200.

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

We apply Equation D.1 to quantify the impact of *quid pro quo* on domestic quality upgrading 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 quo* 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 2001-2003 as the initial quality measure, we also find that knowledge spillovers due to *quid pro quo* 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 upgrading.

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:

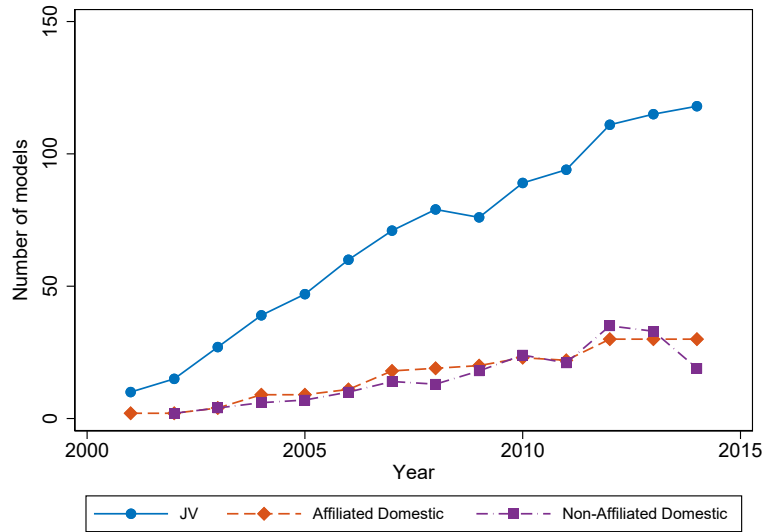
$$q_k = \delta_k + \rho(Q_k - \delta_k) \tag{D.1}$$

$$= \underbrace{(1 - \rho)\bar{\delta} + \rho\bar{Q}}_{\text{Follower's average quality}} + \rho\mu_k + (1 - \rho)\varepsilon_k \tag{D.2}$$

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.

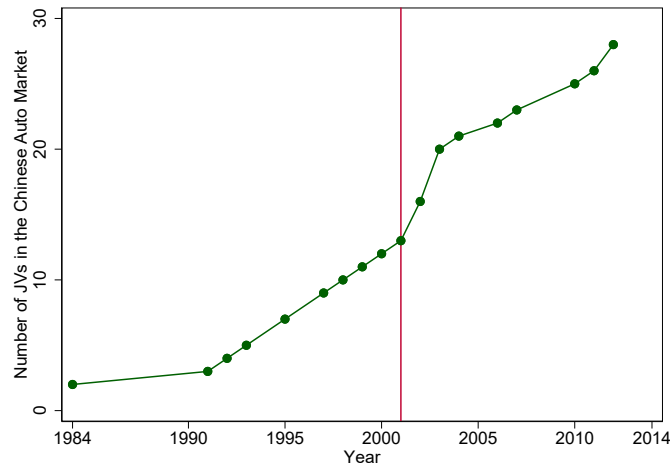
E Figures and Tables

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



Notes: This 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.

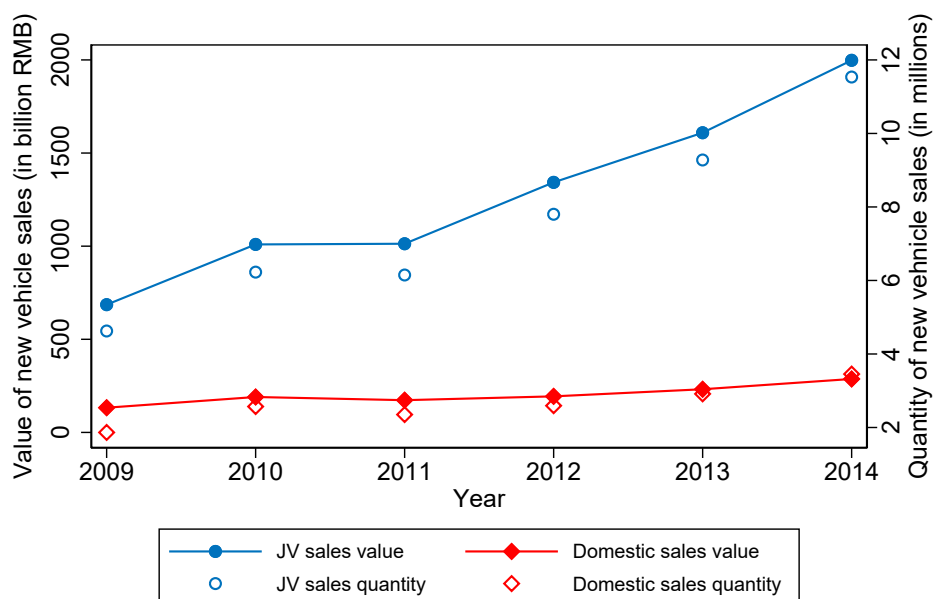
Figure E.2: Entry of Joint Ventures



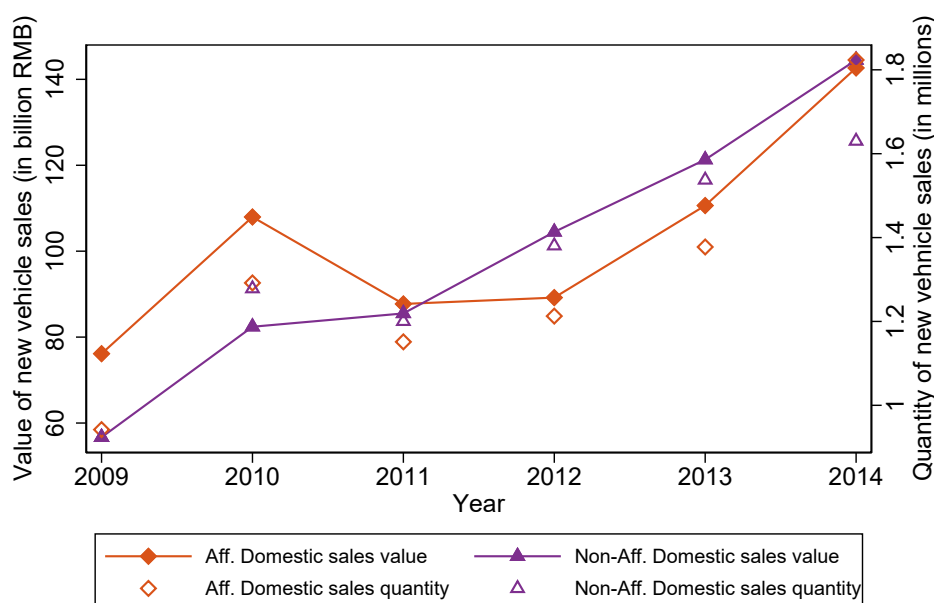
Notes: The figure plots the number of JVs in the Chinese auto market over time. Significant entries include: (1) 1984-1994: VW-Shanghai, VW-FAW, PSA-Dongfeng, Suzuki-Changan; (2) 1994-2000: GM-Shanghai, Honda-Guangzhou, Toyota-FAW, Suzuki-Changhe; (3) post 2000: Ford-Changan, Nissan-Dongfeng, Hyundai-Beijing,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

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

Panel A. Performance of JVs and Domestic automakers



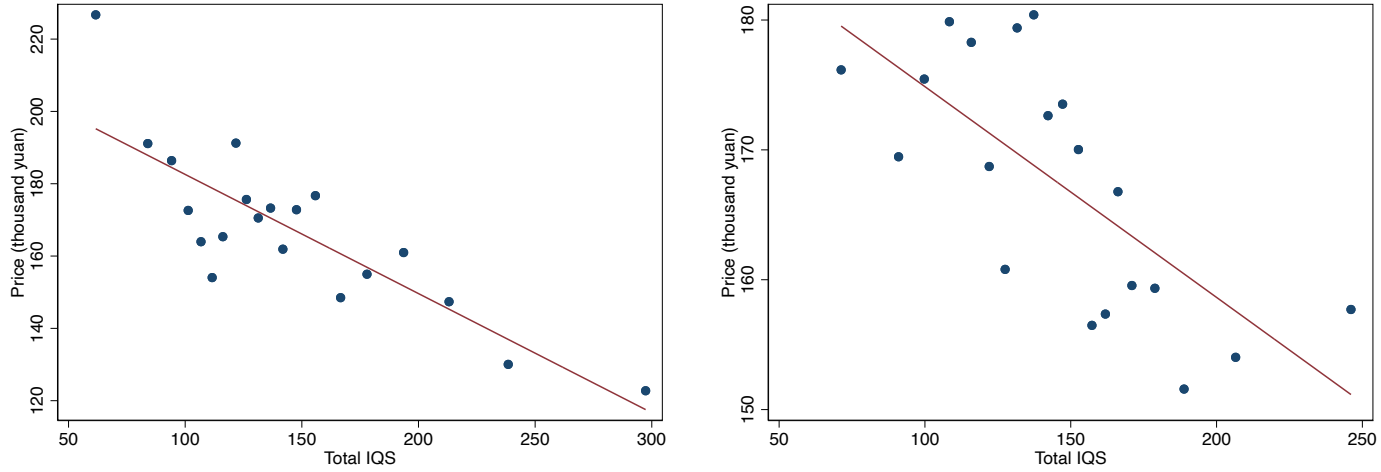
Panel B. Performance among Domestic automakers



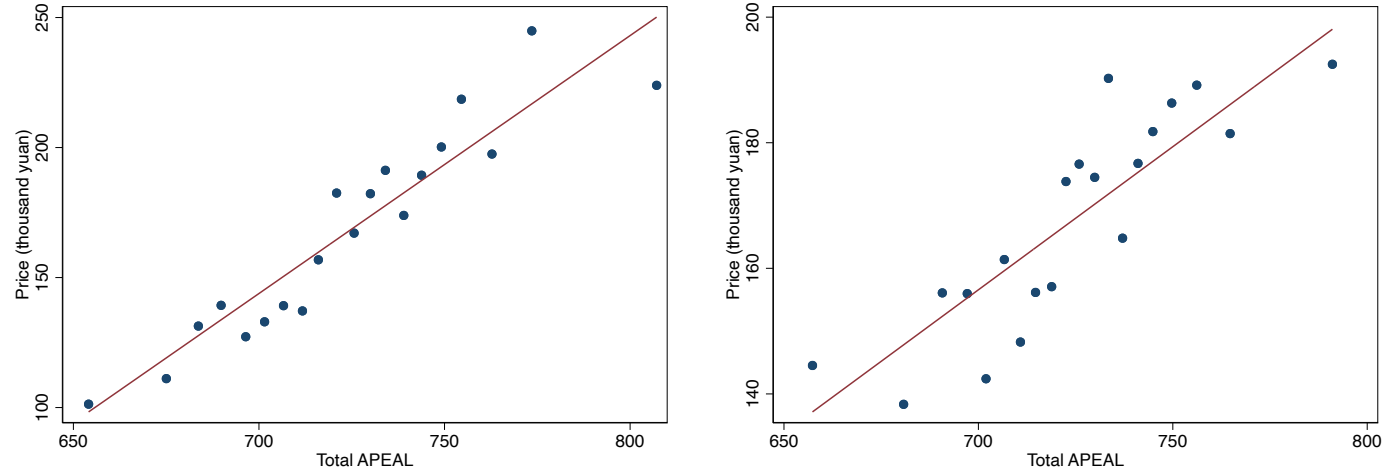
Notes: Sales value and quantity are calculated using the license registration database. The sample contains all models that cumulatively account for 95% of total passenger vehicle sales in China in each year. It does not include imported models, which account for around 3% of total sales.

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

Panel A. Vehicle Price vs. IQS

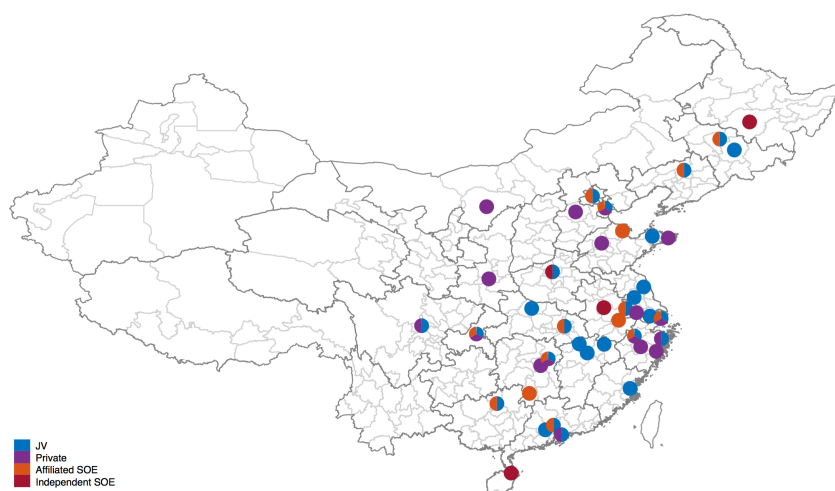


Panel B. Vehicle Price vs. APEAL



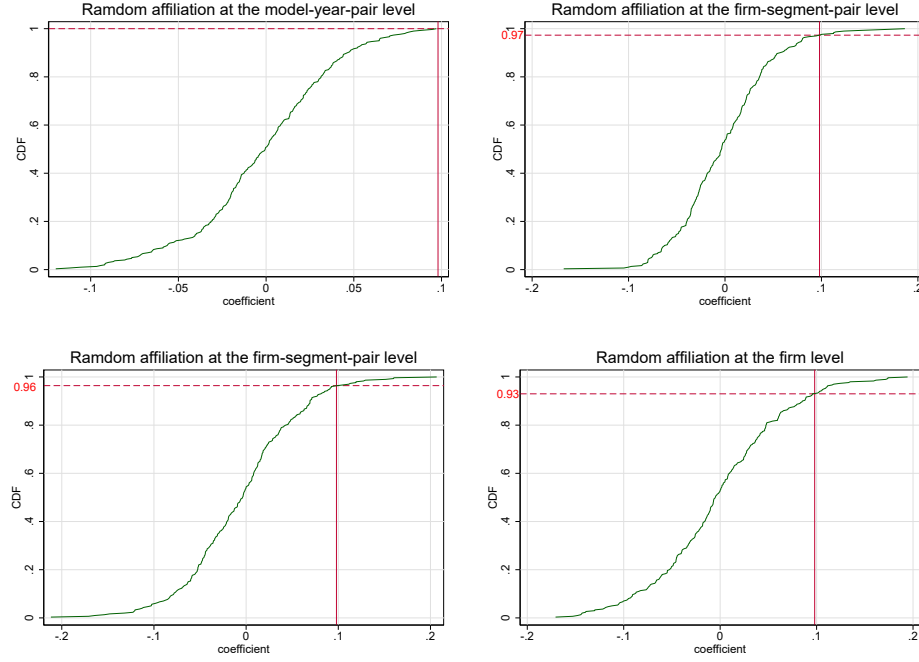
Notes: The figures are binned scatter plots between price and the IQS score (Panel A) and between price and the APEAL score (Panel B) based on data from 2009 to 2014. The price data are only available since 2009. The left figures control for vehicle size and horsepower/weight. The right figures further 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



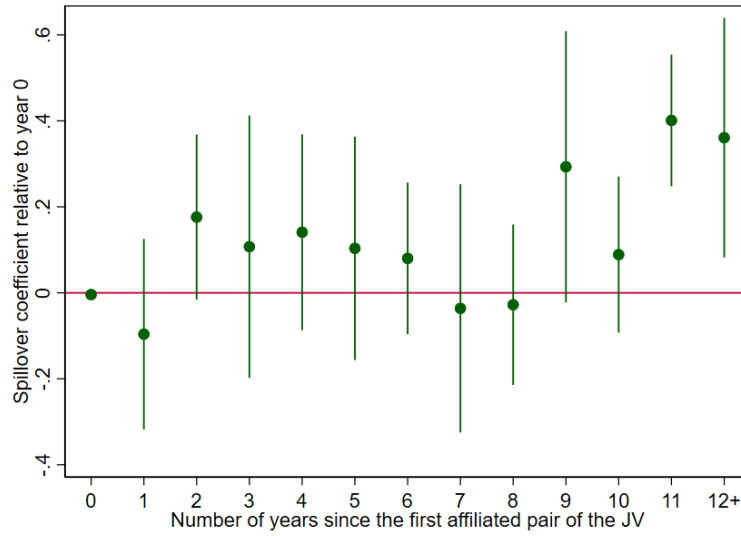
Notes: This figures shows a map of vehicle production sites in China. Each circle represents a city. Colors of the circle indicate the ownership composition of the production plants located in a given city.

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. 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	.111
VW-Shanghai	Volkswagen	Shanghai Auto	1633	.109
GM-Shanghai	General Motors	Shanghai Auto	1510	.101
Hyundai-Beijing	Hyundai	Beijing Auto	1067	.071
Nissan-Dongfeng	Nissan	Dongfeng Motors	920	.061
Ford-Changan	Ford	Changan Auto	853	.057
Citroen-Dongfeng	PSA	Dongfeng Motors	658	.044
Toyota-FAW	Toyota	First Auto Works	568	.038
Kia-Yueda-Dongfeng	Kia Motors	Dongfeng Motors	562	.037
Honda-Guangzhou	Honda	Guangzhou Auto	424	.028
Toyota-Guangzhou	Toyota	Guangzhou Auto	333	.022
Honda-Dongfeng	Honda	Dongfeng Motors	297	.020
BMW-Brilliance	BMW	Brilliance Auto	259	.017
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		
<i>Total</i>			11598	0.773

Notes: This table shows the sales quantity and market shares of JVs in 2014. Sales are denoted in thousand. Landrover-Chery, Infinity-Dongfeng, Qoros, Citroen-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
<i>Panel A. Northeastern Region</i>				
Changchun	Jilin	Toyota-FAW, VW-FAW, Mazda-FAW	FAW	
Jilin	Jilin	Daihatsu-FAW		
Shanyang	Liaoning	GM-Shanghai, BMW-Brilliance	Brilliance	
Haerbin	Heilongjiang		Hafei	
<i>Panel B. Northern Region</i>				
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
<i>Panel C. Eastern Region</i>				
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		
<i>Panel D. Southern Region</i>				
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	
<i>Panel E. Central Region</i>				
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
<i>Panel F. Southwestern Region</i>				
Chongqing	Chongqing	Ford-Changan, Suzuki-Changan	Changan	Lifan
Chengdu	Sichuan	Toyota-FAW, VW-FAW		Geely
<i>Panel G. Northwestern Region</i>				
Xian	Shannxi			BYD

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

	(1)	(2)	(3)
US Score	-0.002* (0.001)	-0.002 (0.001)	-0.002 (0.001)
× SameForeignFirm	0.031 (0.021)	0.024 (0.020)	0.023 (0.020)
× SameSeg		-0.004*** (0.000)	-0.004*** (0.000)
× SameForeignFirm × SameSeg		0.059*** (0.014)	0.045*** (0.014)
× SameName			0.115*** (0.042)
<i>Partialing out:</i>			
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 and the number of observations is 1,866,560. 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 (0.003)	-0.002 (0.002)	-0.007** (0.003)	-0.006* (0.003)	-0.007** (0.003)	-0.008** (0.003)
× SameGroup	0.053 (0.046)	0.033 (0.045)	0.004 (0.039)	0.022 (0.042)	0.017 (0.038)	0.021 (0.051)
× SameSeg		-0.008*** (0.002)	0.035** (0.017)	0.022** (0.011)	0.031* (0.016)	0.032*** (0.011)
× SameGroup × SameSeg		0.127** (0.047)	0.116** (0.056)	0.093** (0.044)	0.113** (0.052)	0.145** (0.057)
<i>Controlling for:</i>						
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). The number of observations is 739,001. 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 (0.001)	-0.000 (0.002)	0.000 (0.008)	-0.001 (0.003)
x SameGroup	0.008 (0.015)	0.004 (0.016)	-0.010 (0.018)	0.010 (0.019)
x SameSeg	-0.013*** (0.004)	-0.017** (0.008)	-0.008 (0.008)	-0.012*** (0.004)
x SameGroup x SameSeg	0.184** (0.071)	0.212** (0.092)	0.185** (0.080)	0.192** (0.079)
Observations	145,370	227,490	282,906	440,046
<i>Partialing out:</i>				
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 partialled 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 levels in columns (2) to (4). Standard errors are clustered at the follower firm-dimension and leader firm-dimension level in Column (1) because the number of firm-categories is too small. *** 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 (0.001)	-0.000 (0.000)	-0.001 (0.002)
× SameGroup	0.016 (0.010)	0.008 (0.009)	0.025 (0.018)
× SameSeg	-0.005*** (0.001)	-0.006*** (0.001)	-0.004** (0.002)
× SameGroup × SameSeg	0.087*** (0.018)	0.103*** (0.026)	0.072*** (0.024)
Observations	717,500	341,073	376,427
<i>Partialling out:</i>			
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* (0.003)	-0.009** (0.004)	-0.005 (0.007)	-0.006 (0.011)
× SameGroup	0.099*** (0.028)	0.159*** (0.041)	0.076** (0.029)	0.103** (0.040)
Observations	130,530	130,530	97,147	97,147
<i>Partialling out :</i>				
Model-Year FE	✓	✓	✓	✓
Segment-Dimension-Year FE	✓	✓	✓	✓
Sample size above 50			✓	✓
Kleibergen-Paap Wald rk F-statistic		154		177

Notes: JD Power divides the underlying survey sample 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 partialled out. Standard errors are clustered at the follower firm-category, 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 (0.003)	-0.001 (0.001)	-0.001 (0.001)
× SameGroup	0.016 (0.010)	0.016 (0.022)	0.016 (0.028)	0.016 (0.015)
× SameSeg	-0.005*** (0.001)	-0.005 (0.006)	-0.005*** (0.001)	-0.005*** (0.001)
× SameGroup × SameSeg	0.087*** (0.018)	0.087*** (0.027)	0.087* (0.051)	0.087** (0.036)
<i>Clusters:</i>				
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. The number of observations is 717,500. 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 (0.018)	0.016 (0.021)	0.016 (0.022)
× SameSeg	-0.005** (0.002)	-0.005** (0.002)	-0.005** (0.002)
× SameGroup × SameSeg	0.087** (0.040)	0.087** (0.041)	0.087** (0.038)
<i>Bootstrap block:</i>			
Model–year–category	✓		
FirmSeg–year–category		✓	
Firm–year–category			✓

Notes: The number of observations is 717,500. 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: Placebo Test using Foreign Partner Overlaps

	(1)	(2)
JVScore	0.000*** (0.000)	-0.000 (0.001)
× SameSeg	0.001*** (0.000)	-0.004*** (0.001)
× PlaceboAffiliation	-0.009** (0.004)	-0.008* (0.004)
× PlaceboAffiliation × SameSeg	-0.037* (0.022)	-0.032 (0.022)
× SameGroup		0.015 (0.010)
× SameGroup × SameSeg		0.086*** (0.019)
<i>Partialling out:</i>		
Model-year FE	✓	✓
Dimension-Segment-Year FE	✓	✓

Notes: The dependent variable is the quality score of a domestic model. The sample includes all pairs of models produced by JVs and domestic automakers. The unit of observation is a pair-year-quality dimension and the number of observations is 717,500. Both leader (JV) and follower (domestic) scores are residualized scores after partialling out model-year fixed effects and dimension-segment-year fixed effects. The definition of PlaceboAffiliation is illustrated in Section B.5. Column (1) repeats our preferred specification in Column (2) of Table 3, replacing true affiliations with placebo affiliations. Column (2) combines true and placebo affiliations in a single analysis. Standard errors are clustered at the follower firm-dimension and leader firm-dimension 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.11: Spillovers via Ownership and Geographical Networks

	(1)	(2)	(3)
JVScore	-0.006* (0.003)		
× SameGroup	0.097*** (0.030)		
× SameGroup × SameProv		0.114** (0.047)	0.057 (0.040)
× SameGroup × DiffProv		0.080** (0.030)	-0.001 (0.039)
× DiffGroup × SameProv		0.037 (0.069)	0.037 (0.068)
× DiffGroup × DiffProv		-0.006** (0.003)	-0.006 (0.004)
× WorkerFlow			-0.001 (0.003)
× SameGroup × WorkerFlow			0.025*** (0.008)
<i>Partialling out:</i>			
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 and the number of observations is 138,540. Both leader (JV) and follower (domestic) scores are residualized scores after model-year and dimension-segment-year fixed effects are partialled 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). WorkerFlow is a standardized measure of the number of workers who moved from a JV to a domestic automaker. 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.12: Overlapping Consumer Base with Poisson Regressions

	(1)	(2)	(3)	(4)
SameGroup	-0.827*** (0.065)	-0.786*** (0.102)	0.032 (0.104)	-0.155 (0.104)
SameSegment		1.808*** (0.028)	1.508*** (0.049)	1.044*** (0.049)
SameGroup $\times$ SameSegment		-0.142 (0.130)	0.157 (0.136)	0.055 (0.136)
SameOwnershipType			1.206*** (0.034)	1.033*** (0.034)
SameSegment $\times$ SameOwnershipType			0.299*** (0.059)	0.112* (0.059)
SameFirm			0.064 (0.046)	-0.308*** (0.052)
<i>Control for:</i>				
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 and the number of observations is 196,225. 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.13: Brand Awareness and Knowledge Spillovers

	(1)	(2)	(3)
JVScore	-0.006* (0.003)	-0.006 (0.004)	-0.006* (0.003)
× SameGroup	0.114*** (0.037)	0.163** (0.079)	
× SameGroup × BrandAssociation		-0.118 (0.100)	
× SameGroup × BrandAssociation High			0.019 (0.078)
× SameGroup × BrandAssociation Medium			0.251* (0.125)
× SameGroup × BrandAssociation Low			0.014 (0.061)
<i>Partialing out:</i>			
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 and the number of observations is 137,533. Both leader (JV) and follower (domestic) scores are residualized scores after model-year and segment-dimension-year fixed effects are partialled 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.14: Cumulative Production and Knowledge Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)
JV Score	-0.006* (0.003)	-0.006** (0.002)	-0.006* (0.003)	-0.006** (0.003)	-0.006 (0.007)	-0.006 (0.006)
× SameGroup	0.097*** (0.030)	-0.060 (0.038)	0.099*** (0.031)	-0.071* (0.041)	-0.055 (0.061)	0.087 (0.149)
× SameGroup × log(JV production)		0.070*** (0.017)		0.076*** (0.019)	0.074*** (0.019)	
× SameGroup × log(Domestic production)			0.003 (0.012)	-0.004 (0.012)	-0.006 (0.015)	
× SameGroup × JV share of total production						0.496* (0.274)
× SameGroup × Trend					0.004 (0.013)	0.014 (0.018)
<i>Partialing out:</i>						
Model-year FE	✓	✓	✓	✓	✓	✓
Dimension-Segment-Year FE	✓	✓	✓	✓	✓	✓
<i>Controlling for:</i>						
Total production (cubic polynomial)						✓

Notes: The dependent variable is the quality score of a domestic model. The number of observations is 138,540. 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 partialled out. Interaction terms are the log of cumulative production by the JV and the domestic firm up to the previous year, and the fraction of JV production out of total JV and domestic cumulative production. Variable “Trend” is defined as the current year minus 2014. In column (6), we control for cubic polynomials of total JV and domestic cumulative production. A small number of observations with missing production data are dropped between Columns (2) and (6). 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.15: Mechanism of Knowledge Spillovers: Worker Flow and Supplier Networks

	(1)	(2)	(3)	(4)
JVScore	-0.006* (0.003)	-0.005 (0.004)	-0.006*** (0.002)	-0.008** (0.003)
× SameGroup	0.097*** (0.030)	0.033 (0.028)	0.078** (0.030)	0.046* (0.023)
× WorkerFlow		-0.001 (0.003)		0.008** (0.003)
× SameGroup × WorkerFlow		0.023*** (0.007)		0.019* (0.010)
× SupplierOverlap			0.016*** (0.001)	0.015*** (0.002)
× SameGroup × SupplierOverlap			-0.004 (0.015)	-0.040 (0.031)
Observations	138,540	138,540	128,354	128,354
<i>Partialling out :</i>				
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 partialled 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.

Table E.16: Feature Adoption by JVs and Domestic Firms

	(1) All	(2) All	(3) Core	(4) Core
JVTech	0.001*** (0.000)	0.001 (0.000)	-0.005** (0.002)	-0.003*** (0.001)
× SameGroup	-0.018*** (0.003)	-0.011** (0.005)	0.070 (0.043)	0.037 (0.027)
× SameSeg		0.002 (0.002)		-0.014 (0.015)
× SameGroup × SameSeg		-0.031 (0.039)		0.161 (0.098)
Observations	170,910	170,910	56,970	56,970
<i>Partialing out:</i>				
Model-year FE	✓	✓	✓	✓
Dimension-Segment-Year FE	✓	✓	✓	✓

Notes: The dependent variable is the adoption propensity of a certain technology feature by a domestic model, as described in detail in Section B.6. We consider all pairs of models produced by JVs and domestic automakers between 2004 and 2014. The unit of observation is a model pair-year-tech feature. Columns (1) and (2) use the full sample of nine features. Columns (3) and (4) restrict the sample to three core features related to engine and transmission. Both the leader (JV) and follower (domestic) adoption propensities are residualized scores after controlling for various fixed effects as noted in the table. 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 and leader firm level. *** implies significance at the 0.01 level, ** at 0.05, and * at 0.1.