# The Dynamics of Technology Transfer: Multinational Investment in China and Rising Global Competition*


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**Abstract**

US multinationals form joint ventures in China for market access and lower labor costs. However, these ventures transfer knowledge to Chinese partners and local firms, increasing future competition from China. While multinationals take into account these spillovers, they don't account for the impact on other US firms, potentially leading to over-investment from a US social perspective. We establish three novel empirical facts on spillovers and competition effects. First, Chinese parent firms of joint ventures become larger, export more, and grow technologically similar to their US partners. Second, in industries with more joint ventures, even non-participating Chinese firms grow larger and more technologically advanced. Third, US firms in these industries experience negative impacts on their size, exports, and innovation. We then develop a two-country growth model with oligopolistic competition and endogenous innovation and joint venture decisions. For the US, joint ventures generate short-run gains that are outweighed by long-run losses due to rising competition from China. Large US firms' profits are higher with joint ventures, at the expense of small firms' profits and the real wage. Banning joint ventures from the beginning would have raised US welfare by 1.3 percent but reduced China's by 10 percent, as Chinese firms' productivity growth is substantially delayed.



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# 1. Introduction

Intensifying economic rivalry between the US and China has cast a spotlight on China's economic policies and business practices. A prominent example is the Chinese policy that mandates US multinational enterprises (MNEs) to transfer technology as a condition for market access, typically through the formation of joint ventures with Chinese firms. Critics contend that this constitutes intellectual property theft and exacerbates the trade imbalance between the US and China. In response, the US has imposed restrictions on outward foreign direct investment (FDI) in critical technologies.[1]

However, considering that US firms voluntarily form joint ventures to gain access to the Chinese market and cheaper labor despite the risk of technology leakage, is there an economic justification for restricting joint ventures? When US firms establish joint ventures with Chinese firms, they recognize that these ventures will enhance the productivity of their Chinese partners and other local firms through knowledge spillovers, thereby intensifying global competition in the future. However, they do not account for the dynamic profit losses that other US firms will suffer due to the intensified competition from China. Given the spillovers and competition effect, there may be over-investment in joint ventures and technology transfers relative to what is socially optimal for the US.[2]

Our paper makes two contributions. First, we provide novel empirical evidence of technology spillovers and the competition effect resulting from joint ventures. Second, motivated by these findings, we build a two-country endogenous growth model in which oligopolistic firms strategically make innovation and joint venture decisions, and we analyze the full dynamics of the model. Our quantitative analysis shows that there are indeed too many joint ventures in equilibrium because leading US firms do not take into account the negative competition effect on other US firms.

For the empirical analysis, we construct our dataset by merging Chinese firm-level balance sheet data from the National Bureau of Statistics, patent data, and ownership structure information from Orbis. For US firms, we use Compustat. From this comprehensive dataset, we establish three empirical facts on the impact of joint ventures.

First, we find a *direct* positive effect of joint ventures on Chinese parent firms (or partners) using an event study design. Specifically, we match Chinese parent firms that establish joint ventures with foreign MNEs (the treated) with firms that have never formed such relationships (the control) through propensity score matching. Following the formation of joint ventures, Chinese parent firms

[1] "As companies negotiate the terms of the joint venture, the foreign side may be asked—or required—to transfer its technology in order to finalize the partnership. Especially in instances where the Chinese partner is a state-owned or state-directed company, foreign companies have limited leverage in the negotiation if they wish to access the market. Although this type of technology transfer may not be explicitly mandated in a Chinese law or regulation, it is often an unwritten rule for market access . . . " (Office of the U.S. Trade Representative, 2018). For example, the Biden administration banned recipients of CHIPS Act funding from certain investments in China (Department of Commerce, 2023).

[2] Multiple examples illustrate negative competition effects. China formed JVs with Kawasaki Heavy Industries and Siemens to develop its high-speed rail network, acquiring key technologies. Over time, Chinese firms enhanced these technologies and competed globally, increasing competitive pressure on their former partners. (Source: Wall Street Journal). Another example is AMD's attempted JV with Tianjin Haiguang Advanced Technology Investment (THATIC) to license x86 chip technology to China. Intel opposed the move, fearing it would undermine its global market shares of 87.7% (Source: Wall Street Journal).

experienced significant growth in sales, capital, and exports. Furthermore, their patenting activities became more similar to those of their foreign partner firms, indicating a direct diffusion of knowledge through the joint venture.

Second, we find evidence of *indirect* spillovers to other Chinese firms that are not part of a joint venture. In sectors with more joint ventures, these firms grew larger and more technologically advanced. To address endogeneity concerns, we use an instrumental variable (IV) strategy with joint venture investments from Japan and Korea to India as instruments. The identifying assumption is that the push and pull factors driving joint venture investments among these three countries are unrelated to those influencing US-China joint ventures.

Last but most important, utilizing the same IV strategy, we find that in sectors with more joint ventures, US firms experienced negative effects on their size and innovation. Our measure of exposure to joint ventures at the sector level explains a significant portion of the trade-based measure of the China shock (Autor et al., 2013).

For the quantitative analysis, we developed a two-country growth model where oligopolistic firms make strategic decisions on innovation and joint ventures. In each sector and country, there are two types of firms: a leader and a fringe firm. All firms from both countries within the same sector produce differentiated varieties, selling domestically and exporting to foreign markets. Leaders can enhance productivity through innovation, and US leaders have the option to establish joint ventures in China, partnering with the Chinese leader firm in the same sector. These joint ventures allow US firms to bypass trade costs and utilize Chinese labor for production. The surplus from these joint ventures is shared between the two parent firms through Nash bargaining.

Even without joint ventures, the model allows for stochastic knowledge diffusion both within and between countries. Once a joint venture is established in China, the probability of knowledge diffusion from the US parent firm to the Chinese parent firm increases, consistent with our empirical finding on the direct effect. As a result, the surplus from a joint venture includes not only the flow profit of the joint venture firm but also the value of the higher probability of knowledge diffusion to the Chinese parent firm. Additionally, Chinese fringe firms, which do not participate in any joint venture by construction, indirectly benefit. This is because there is an additional source of knowledge diffusion—the joint venture firm itself—within the sector, and the Chinese parent firm is likely to have higher productivity after forming the joint venture. This aligns with our empirical finding of the indirect effect.

The entry of a new joint venture firm immediately intensifies competition in the sector. The stochastic knowledge diffusion to the Chinese leader and the fringe firm further intensify competition over time. The US leader takes all these effects into account when making the joint venture decision. It also partially captures the profit flow of the joint venture and the spillover benefits to the Chinese leader through bargaining. However, it ignores the negative effects of heightened competition on the profits of its domestic competitor, the US fringe firm. Our third empirical finding above is a manifestation of this negative effect.

We solve for the model's transitional dynamics from an initial state, where Chinese firms have lower productivity than US firms, to a balanced growth path. We calibrate the model to the empirical moments along the transition path. Notably, we infer the model parameters governing knowledge diffusion from the regression coefficients that we present as evidence of spillovers in our empirical analysis.

US leaders benefit from joint ventures in the short run through lower trade costs for serving the Chinese market and lower wages in China. They also partly capture the value of technology transfer to Chinese leader firms through bargaining. Over time, however, Chinese firms catch up faster due to the knowledge diffusion facilitated by these joint ventures, and the heightened competition negatively affects US leaders. Nevertheless, the present discounted value of US leaders' profits is higher with joint ventures—otherwise, they would not invest in them. For US fringe firms, leader firms' joint ventures have only a negative effect on their profits, through intensified competition from China.

Joint ventures have two opposing effects on the innovation efforts of US leaders. On the one hand, the increased probability of knowledge diffusion to China means that profits from successful innovations are smaller and shorter-lived, which may reduce innovation efforts. On the other hand, the option to from a joint venture makes US leaders innovate more, because their innovation increase additional profits from joint ventures and bargaining fees they receive from Chinese leaders. In our quantitative analysis, the former dominates at least in the medium run, so US leaders innovate less with joint ventures. For Chinese leaders, knowledge diffusion serves as a substitute for their own innovation efforts, and they innovate less with joint ventures.

The value and hence the likelihood of forming joint ventures for US leaders are higher when the US-China technology gap is larger. Since joint ventures reduce the technology gap between the US and Chinese firms through knowledge diffusion, they have the effect of eroding the overall comparative advantage of the US. Partly for this reason, in the aggregate, joint ventures lead to lower real wages in the US. As US leaders shift some of their production to China, the reduced labor demand translates into lower wages in the US. Although joint ventures and the knowledge diffusion that they engender do reduce the price of goods, this reduction is not sufficient to prevent the real wage from falling.

To compute the welfare consequences of joint ventures, we calculate the effect of a policy that prohibits them from the beginning (in 1999). We find that prohibiting joint ventures increases US welfare by 1.3 percent in units of permanent consumption. For the US, leaders' profits fall by 27 percent in present value terms, while fringe firms' profits increase by 5.1 percent; however, total profits decline. Yet, the real wage increases by 2.6 percent due to higher labor demand in the US, leading to the overall welfare gain. The ban has a transitory negative effect, because US firms cannot immediately benefit from lower wages in China and reduced trade costs via joint ventures. However, this effect is outweighed by medium-run benefits, as the US maintains its technological advantage over China for longer, driven by higher innovation efforts and less technology leakage to China.

As for China, when the US bans joint ventures, Chinese leader firms compensate for reduced knowledge diffusion by increasing their own innovation efforts. However, China's productivity growth is substantially delayed, and the absence of joint ventures reduces China's welfare by 10 percent in units of permanent consumption. The profits of both leaders and fringe firms, as well as the real wage, are lower without joint ventures from the US.

To better understand the source of over-investment in joint ventures, we consider an alternative scenario in which US leader firms must compensate the fringe firms for their losses incurred due to joint ventures. With such multilateral bargaining, significantly fewer joint ventures are formed. Moreover, banning joint ventures in this setting actually decreases US welfare, suggesting that the failure to account for the profit losses of other US firms is a key source of inefficiency from joint ventures, and that coordinated joint venture decisions are preferable to a ban on them.

Our result does not mean that banning joint ventures is *always* welfare-enhancing for the US. If we were to prohibit new joint ventures starting in 2025, when the technology gap between the US and China is much smaller than in 1999, the competition effect through spillovers would be reduced, which would lessen the inefficiency from joint ventures. In this case, the loss of short-run gains from joint ventures (market access) is relatively large, and the medium-run boost to innovation efforts is small enough that banning joint ventures would reduce US welfare.

**Related literature.** First, our paper contributes to the literature on trade and innovation with knowledge diffusion across countries (e.g., Grossman and Helpman, 1993; Atkeson and Burstein, 2010; Impullitti, 2010; Sampson, 2016, 2023; Buera and Oberfield, 2020; Perla et al., 2021; Cai et al., 2022; Somale, 2021; Atkin et al., 2024; Santacreu, 2015, 2024; de Souza et al., 2025). Researchers have incorporated FDI into endogenous growth models (Branstetter and Saggi, 2011; He and Maskus, 2012; Acemoglu et al., 2015; Rodríguez-Clare, 2010). Our model builds on Akcigit et al. (2023) and Choi and Shim (2024), where firms compete with foreign firms through innovation but also benefits from knowledge diffusion. We extend this framework by incorporating the idea that multinational production facilitates knowledge diffusion from advanced to developing countries (e.g., Burstein and Monge-Naranjo, 2009; Holmes et al., 2013). Milicevic et al. (2025) study endogenous knowledge spillovers across countries through FDI and how FDI can facilitate R&D coordination. Our contribution lies in studying the negative competition effects of multinational activities on other firms through technology leakages and quantitatively analyzing the implications of recent policies. Akcigit et al. (2024) discuss technology leakages in the context of Chinese venture capital investment in the US and national security concerns.[3] We empirically demonstrate the negative economic impacts of joint ventures on domestic firms and quantitatively show that the policy implications can differ between the short and the long run. König et al. (2022) examine the dynamic effects of misallocation on TFP growth in China using closed-economy growth model with innovation and learning from random interactions.

[3] Lam (2024) focuses on technology leakage to China through illegal imitation and studies optimal intellectual property rights protection.

We show that joint ventures were an important source of learning for Chinese firms.

Recent quantitative trade models have studied implications of multinational production on global trade and growth (e.g., Irarrazabal et al., 2013; Keller and Yeaple, 2013; Antràs et al., 2017; Cravino and Levchenko, 2017; Boehm et al., 2019; Head and Mayer, 2019; Wang, 2021; Garetto et al., 2024). Our model focuses on the interaction between two countries, but it preserves key ingredients of multinational production such as proximity-concentration trade-offs (Helpman et al., 2004) and the role as export platform (e.g. Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017; Arkolakis et al., 2018). Fan (2024) studies offshoring in R&D and Ma and Zhang (2023) analyze the effects of the quid pro quo policy building on the framework of Holmes et al. (2013). Unlike previous studies, our model highlights the dynamic trade-off between static market gains and risks of technology leakages for MNEs. Strategic interactions in MNE activities have been under-explored in the literature, with the exception of Knickerbocker (1973) and Head et al. (2002), who study their role in the extensive margins of MNE activities. Our model further highlights the importance of dynamic strategic interactions between and within countries in FDI activities and technology transfers.

Third, our empirical findings contribute to the empirical literature on the knowledge diffusion through FDI, which has been reviewed by Harrison and Rodríguez-Clare (2010). Our evidence of the direct effects on Chinese joint venture parent firms is consistent with Jiang et al. (2023) and Bai et al. (2020). It is also consistent with previous literature that studies within-firm knowledge diffusion channels. Our indirect spillover effects to Chinese firms that do not participate in joint ventures are consistent with previous papers that document positive spillovers from foreign MNEs to domestic firms in host countries.[4] In addition to these findings, we provide novel evidence on indirect negative competition effects of US MNEs' joint ventures on other US firms.[5]

Finally, this paper contributes to the recent literature on the China shock and the decline of the US manufacturing sector (Autor et al., 2013). Our empirical results show that FDI in China improved performance of Chinese firms and made them more competitive in the global market, contributing to declines in US manufacturing employment and innovation.[6]

# 2. Background and Data

## 2.1 Quid Pro Quo Policy and the US-China Trade War

After decades of isolation from the West, Deng Xiaoping initiated economic reforms and opening China's markets and foreign investment in 1979 with the "Law on Sino-Foreign Equity Joint Ventures"

[4]For example, see Javorcik (2004); Keller and Yeaple (2009); Newman et al. (2015); Lu et al. (2017); Alfaro and Chen (2018); Giorcelli and Li (2021); Setzler and Tintelnot (2021); Alfaro-Ureña et al. (2022); Gong (2023); Amiti et al. (2024); **?** for spillovers from FDI or technology transfers.

[5]Aitken and Harrison (1999), and Bao and Chen (2018) document negative competition effects of MNEs' entry on firms in host countries.

[6]There is mixed evidence on the impact of the China shock on firm innovation. Bloom et al. (2016) find positive impacts on European firms, whereas Autor et al. (2020) find negative impacts on US firms. Aghion et al. (2024) find that output shock decreased firms' innovation whereas input supply shock had positive impacts.

(henceforth referred as the JV Law). Joint ventures (JVs) were defined as firms with mixed ownership between foreign and Chinese shareholders, with foreign equity shares between 25% and 100%. Firms with foreign equity below 25% were classified as domestic firms, while those with 100% foreign equity were registered as wholly foreign-owned enterprises (WFOEs). A key difference between JVs and WFOEs is ownership and control. WFOEs are 100% owned and controlled by foreign MNEs, granting them full autonomy over operations and decision-making. In contrast, JVs require shared ownership between foreign MNEs and local Chinese partners. Foreign firms were often required to transfer technology to their local partners, and profits from JVs were shared based on equity stakes. Equity shares were strictly regulated, with minimum requirements and maximum caps on foreign MNE ownership.

The quid pro quo policy emerged alongside JVs, requiring foreign MNEs to transfer technologies, capital equipment, know-how, and product lines as part of their equity contribution (the quid) in exchange for access to China's large consumer market and abundant labor (the quo).[7] From 1979 to 1986, JVs were the only legally permitted form of FDI in China, although WFOEs were gradually allowed in some sectors starting in 1986. Following China's WTO accession in 2001, the Chinese government introduced major FDI policy reforms, along with tariff liberalization and enhanced intellectual property protections, to comply with WTO obligations. Although explicit technology transfer mandates were banned and JV requirements eased after WTO accession, equity caps and JV requirements persisted in many high-tech sectors.[8]

Despite these post-WTO reforms, the quid pro quo policy has long been criticized by the US policymakers as an unfair trade practice. They have argued that it has persisted in more implicit forms.[9] This criticism intensified with China's rapid growth, being the second largest economy, and the launch of "Made in China 2025", an industrial policy introduced in 2015 to accelerate the development of China's high-tech sectors. This initiative further raised concerns for national security and technology rivalry among US policymakers, reinforcing the view that the quid pro quo policy remains central to its industrial strategy, especially in high tech sectors. Amid rising geopolitical tensions, in 2018, the US imposed tariffs on over $250 billion of Chinese goods, expanded the Entity List for Chinese firms, and, under the Biden administration, barred CHIPS Act recipients from certain investments in China.

[7]The JV Law explicitly stated: *"The technology and equipment contributed by a foreign joint venturer as its investment in kind must be advanced technology and equipment that suit China's needs."*

[8]Since 1995, "Catalogue for the Guidance of Foreign Investment Industries" (henceforth the Catalogue) provided guidelines for regulations on FDI. Although this Catalogue became more liberal with revisions in 1997, 2002, 2004, 2007, and 2012, still many high-tech sectors or sectors related to national security were subject to the regulation. For example, in 2017, in the automobile industry, the Chinese partner's ownership share could not fall below 50%. Airplane manufacturing was restricted to JVs, while rare earth exploration, mining, and processing remained completely closed to foreign investment.

[9]In its 2017-18 Section 301 investigations, the Office of the United States Trade Representative reported that China implicitly pressured foreign MNEs to form JVs and transfer advanced technologies through both formal regulations and informal administrative barriers.

## 2.2 Data

We construct the main dataset by merging balance sheet, ownership structure, and patent data for Chinese and US manufacturing firms, along with sectoral data, covering 1998-2013. All monetary values are in 2007 USD. Appendix A.1 describes the data construction in detail.

We obtain the Chinese firm balance sheets from the Annual Survey of Industrial Enterprises, constructed by the National Bureau of Statistics. They have annual data on firm sales, exports, employment, and capital (measured as fixed assets), their affiliated 4-digit 1994 Chinese Industry Classification (CIC) codes, location of all state-owned and private firms with sales exceeding 5 million Renminbi before 2010 and 20 million since 2011.[10] To ensure consistency, we apply the 20 million RMB threshold throughout the sample period. The data is representative at the national level, which accounts for 90% of total Chinese manufacturing output. The dataset has information on firm registration types including JVs, WFOEs, state-owned firms, and domestic private firms. In our definition of JVs and WFOEs, we exclude those involving foreign MNEs from Hong Kong, Macao, and Taiwan, given the special economic and regulatory relations between mainland China and these regions.

We also supplement the Chinese balance sheet data with the Chinese Customs Trade Statistics from 2000 to 2013.[11] It has information on firm-level imports and exports at the country-product (HS 8-digit code) level.

We obtain US firm consolidated balance sheet from US Compustat that covers publicly listed firms, including sales, employment, capital (measured as PPEGT), and R&D expenditures. We also obtain each firm's total foreign sales (including both exports and sales from foreign affiliates) from the historical geographic segment data and use this variable as a proxy for exports.[12] A firm's industry affiliation is classified under 4-digit 1987 SIC codes. We follow Autor et al. (2013) to aggregate these codes up to 383 4-digit codes for compatibility with the Chinese CIC and HS codes. We use the concordance from Ma et al. (2014) to map CIC to SIC codes.

Although the Annual Survey of Industrial Enterprises identifies whether firms are FDI affiliates (JVs or WFOEs) or not, it does not have information on their ownership links between Chinese partners and foreign MNEs. To identify these links, we use historical ownership data from the Orbis Global database. We clean the data following Kalemli-Ozcan et al. (2024). We match these ownership linkages with the Chinese firm data using the unified social credit identifier and firm names.[13] The dataset also has information on equity shares of each engaged party.

We obtain patent data for Chinese firms granted by the China National Intellectual Property

[10] Brandt et al. (2012) provides a more detailed description of the dataset.

[11] The customs records and our Chinese firm balance sheet data do not share common firm identifiers. Following standard practices (e.g. Chor et al., 2021), we merge these two datasets using firm names, phone numbers, and addresses. Also, see Manova and Zhang (2012) for more detailed description of the dataset.

[12] US publicly-listed firms need to disclose foreign sales when they are material. According to SFAS No. 131, they have to separately report sales for operating segments if they account for 10% or more of total sales, which is the source of information in the historical segment data.

[13] We first match firms in the two datasets using the unified social credit identifier, which provides the majority of mappings. Then, we match firms based on firm names through the Orbis interface's batch search function.

Administration (CNIPA) from the Google Public Patent Database and for US firms from the United States Patent and Trademark Office (USPTO). Among the three patent types, innovation, application, and appearance design, we include only innovation patents, as is standard in the literature. From these datasets, we construct firm-level counts of yearly new patents and cumulative patent stock across 875 3-digit International Patent Classification codes.

We obtain sectoral data for US manufacturing from the NBER-CES Manufacturing Industry Database and bilateral trade data from Comtrade (Gaulier and Zignago, 2012). We map Comtrade trade data to the NBER-CES database by converting HS 6-digit codes into 1987 SIC 4-digit codes following Pierce and Schott (2012).

Appendix Tables A1 and A2 report the the descriptive statistics of US and Chinese firms, respectively. US MNEs and Chinese JV partners were larger than their peers. Chinese JV partners were also disproportionately state-owned, reflecting the government's active role in JV formation.[14] JV and WFOE subsidiaries were also bigger other firms in size.

## 3. Motivating Facts

In this section, we present three motivating facts on JVs. First, JV formation directly improved the performance of Chinese partner firms. Second, JVs generated positive spillovers to other Chinese firms that did not participate in JVs. Third, we show that these gains among Chinese firms intensified competitive pressures on US firms.

### Fact 1. Direct Effects of JV Formation on Chinese Partner Firms

To examine the direct effects, we compare a treated group (Chinese firms that formed JVs with foreign MNEs) to a control group (those that did not form any JVs) before and after they formed their first JV relationship. To mitigate endogeneity due to selection, we construct the control group using propensity score matching. Each year, firms that formed JVs serve as treated observations, while those that never formed JVs serve as control observations. Pooling these observations across all years, we estimate the propensity score, the probability of forming a JV, using a logit model with firm-size related observables as covariates. These observables include log sales, log capital, log employment, dummies of exporting and positive patent stock, inverse hyperbolic sine transformation of exports and patent stock, and year fixed effects. For each treated firm, we match up to 4 control firms from the same year and 2-digit industry with the closest propensity score, allowing replacements so that a control firm can be matched to multiple treated firms.

[14] Many strategic and high-tech sectors in China are dominated by state-owned firms under the mandate of the State-owned Assets Supervision and Administration Commissions. The Commissions listed key sectors—which are considered to be important for national security and the economy—where the state must retain absolute control, including oil and petrochemicals, telecommunications, transportation equipment, and shipping. For example, GM was the first US automaker to form a JV in China. In 1997, it partnered 50:50 with the state-owned Shanghai Automotive Industry Corporation to launch Shanghai GM.

The matching procedure results in 176 matches with 176 and 692 unique treated and control group firms. The matched treated and control groups are well-balanced across observables, including various size measures, labor productivity, patenting activity, and exporting status (Appendix Table B1). Furthermore, a balance test—regressing the treatment dummy on these pre-event observables—confirms that none of these observables significantly predict treatment status (Appendix Table B2). Additionally, raw data plots reveal no differential pre-trends between the two groups before the event, with the outcomes of the two groups starting to diverge only after the event (Appendix Figure B2).

Using the constructed matches, we estimate the following event study specification:

$$y_{imt} = \sum_{\tau=-5}^{7} \beta_\tau \left( D_{mt}^{\tau} \times \mathbb{1}[\text{JV Partner}_{it}] \right) + \delta_{im} + \delta_{mt} + \varepsilon_{imt} \tag{3.1}$$

where $i$ denotes firm, $m$ match, and $t$ year. $D_{mt}^{\tau}$ are event study dummies defined as $D_{mt}^{\tau} \equiv \mathbb{1}[t - \tau = t(m)]$, where $t(m)$ is the event year of match $m$. $\mathbb{1}[\text{JV Partner}_{it}]$ is a dummy for forming first JVs. We normalize $\beta_{-1}$ to zero. $\delta_{im}$ and $\delta_{mt}$ are match-firm and match-year fixed effects.[15] $\varepsilon_{imt}$ is an error term. Standard errors are two-way clustered at the match and firm levels, which account for mechanical correlations in residuals introduced by matching with replacement, as the same firm may appear multiple times.

We consider four dependent variables: log sales, log capital, inverse hyperbolic sine transformation of exports, and a measure of technological proximity to foreign MNEs. The first three variables capture firm size and performance in global markets. The technological proximity variable measures the extent to which Chinese partners became technologically similar to their foreign MNE counterparts after forming JVs. If Chinese firms acquired knowledge from foreign MNEs through JV partnerships, we would expect an increase in their technological similarity to these foreign partners over time.

Following the literature, we calculate technological proximity based on cosine similarity using patent data, as patents reflect their technological capabilities[16]:

$$\text{Technological proximity}_{imt} = \frac{F_{imt}^{\top} F_{\text{MNE}(i),t(m)}}{(F_{imt}^{\top} F_{imt})^{0.5} (F_{\text{MNE}(i),t(m)}^{\top} F_{\text{MNE}(i),t(m)})^{0.5}}. \tag{3.2}$$

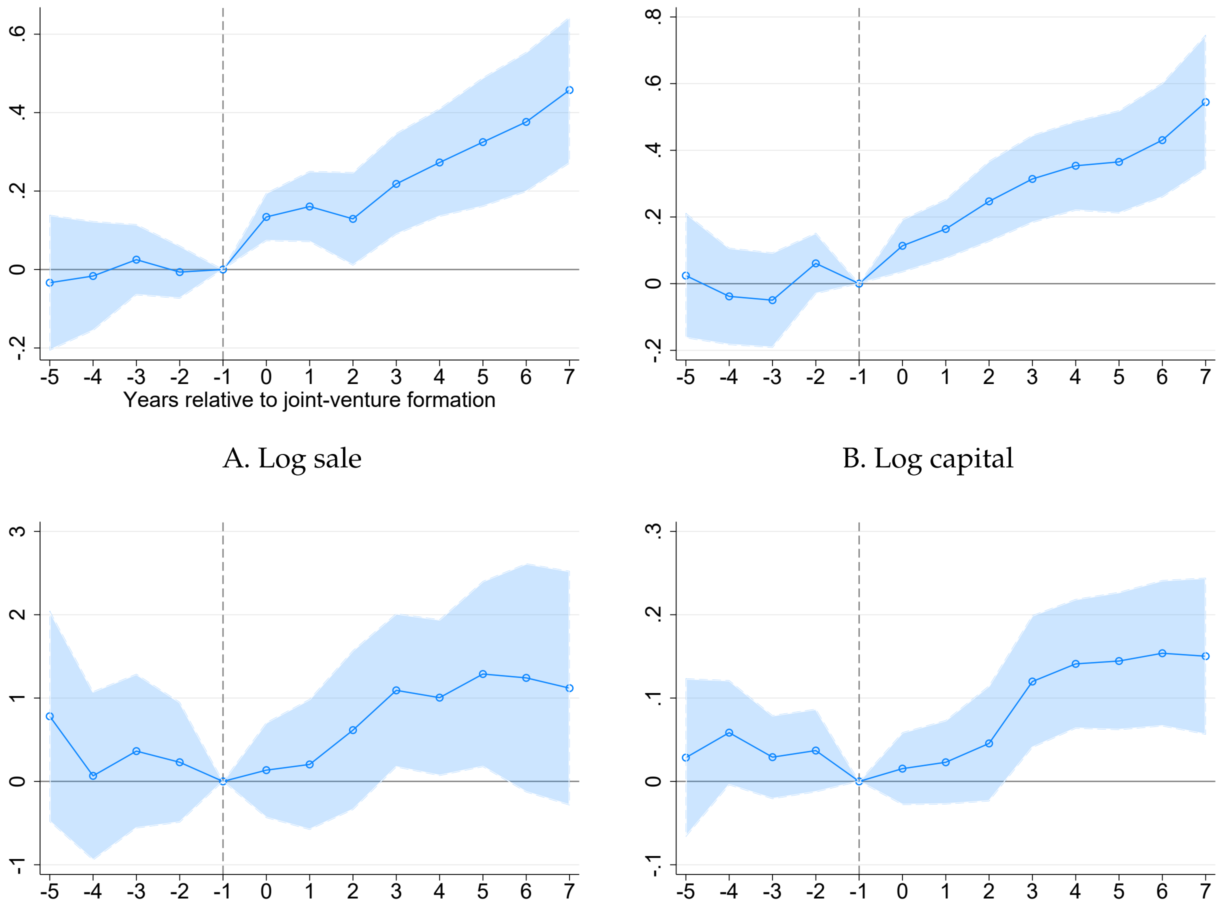
$F_{imt} = (p_{i1t}, \ldots, p_{iKt})^{\top}$ is a vector where the $k$-th element represents Chinese firm $i$'s patent stock (under the Chinese patent system) in $k$-th technological fields within match $m$ and year $t$.[17] Similarly,

[15] The specification is fully-stacked event study design that does not suffer from issues studied by the recent staggered diff-in-diff literature (e.g. Roth et al., 2023).

[16] For the proximity measure to be well-defined, we require that both foreign MNEs and Chinese partners to have engaged in patenting activities. Therefore, we restrict our sample of Chinese partners to be those who ever patented to the Chinese patent system and foreign MNEs to those who ever patented to USPTO. The matching applied to this restricted sample resulted in 176 matches with 176 and 692 unique treated and control group firms.

[17] When calculating proximity, we assign greater weights to more recent patents by applying an R&D depreciation rate of 0.3 (Li and Hall, 2020). Specifically, we compute $F_{imt}$ as: $F_{imt} = \text{New patent}_{imt} + 0.7 \times F_{im,t-1}$, where $\text{New patent}_{imt}$ is a vector of new patents across technological fields.Our results remain robust to alternative depreciation rates ranging from 0 to 0.5 (cols. 7-9 of Appendix Table B4). Similar measures have been used in prior studies to calculate technological

Figure 1: Direct Effects of Joint Venture Formation on Chinese Partners




A. Log sale

B. Log capital

C. Ihs export

D. Technological proximity

**Notes:** This figure illustrates the event study estimation results of equation (3.1). 95% confidence intervals, based on standard errors two-way clustered at the match and firm levels, are reported. $\beta_{-1}$ is normalized to zero. In Panels A, B, C, and D, the dependent variables are log sales, log capital, inverse hyperbolic sine transformation of exports, and technological proximity (equation (3.2)), respectively. All specifications include firm-match and match-year fixed effects. In Panel D, the sample size decreases due to firms with zero patent stock, as technological proximity is only well-defined for firms with positive patent stock in both the treated and control groups.

$F_{\mathrm{MNE}(i),t(m)}$ represents foreign MNEs' patent stock from the USPTO, measured at the event year $t(m)$, making it fixed over time. Because $F_{\mathrm{MNE}(i),t(m)}$ is fixed over time, any changes in the technological proximity reflect only Chinese partners' patenting activities. We use different patenting systems for Chinese partners and foreign MNEs because Chinese firms rarely patent with the USPTO, while the US patent system serves as a better measure for the technological frontier of MNEs. Higher values indicate greater technological proximity between Chinese partners and MNEs.

**Estimation results.** Figure 1 reports the results (see cols. 1-4 of Appendix Table B3 for more details). 4 years after forming JVs for the first time, Chinese partners' sales and capital increased by 27% and

proximity between firms (e.g. Branstetter, 2006; Bloom et al., 2013; Akcigit et al., 2016).

35%, with improvements in export performance. Importantly, they technologically became close to their foreign MNE counterparts. These findings suggest that their improved performance is related to technological diffusion from foreign MNEs.

We consider a battery of robustness checks. Forming JVs also had positive impacts on alternative outcomes of log employment, export dummies, cumulative patents and yearly new patents (cols. 5-8 of Appendix Table B3). The results remain robust to mild violations to the parallel pre-trend assumption, except for exports (Rambachan and Roth, 2023) (Appendix Figure B3). The results are robust to alternative numbers of matches (cols. 1-6 of Appendix Table B4).

### Fact 2. Indirect Positive Spillovers to Chinese Firms

Next, we show that JVs also benefited other Chinese firms that were not directly involved in JV. We consider the following long-difference specification for the period 1999-2012:

$$\Delta y_{fj} = \beta \Delta \mathrm{FDI}_{fj} + \vartheta \mathrm{NTRgap}_j + \mathbf{X}'_{fj}\gamma + \varepsilon_{fj}, \tag{3.3}$$

where $f$ denotes for firm and $j$ 4-digit industry code. The dependent variable $\Delta y_{fj}$ is the DHS growth rates (Davis et al., 1998) of firm-level outcomes: $100 \times \frac{y_{fj,12} - y_{fj,99}}{0.5(y_{fj,12} + y_{fj,99})}$. $\mathbf{X}_{fj}$ are observables. All specifications include dummies of state-owned firms and FDI affiliates, and province fixed effects. $\varepsilon_{fj}$ is the error term. Regression models are weighted by firms' initial sales. Standard errors are clustered at the 3-digit industry level.

$\Delta\mathrm{FDI}_{fj}$ measures sectoral total FDI exposure in China. We focus on total FDI rather than separating JVs and WFOEs for two reasons. First, teasing out indirect spillovers from each FDI type is econometrically challenging, as it requires exogenous variation for each type separately. Because our IV strategy, detailed below, exploits exogenous variation in total FDI, we focus on their combined effects. Second, the only difference between WFOEs and JVs is whether Chinese partner firms are involved or not. However, as long as WFOEs generate indirect spillovers, they can also lead to the negative externality arises because MNEs fail to internalize other firms' profit losses through this indirect spillovers.

$\Delta\mathrm{FDI}_{fj}$ is defined as the change in the total sales of all sector $j$ FDI affiliates (JVs or WFOEs) between 1999 and 2012, normalized by total sector sales in 1998:

$$\Delta \mathrm{FDI}_{fj} = \frac{\Delta \mathrm{FDI\ sales}_{fj}}{\mathrm{Total\ sales}_{j,98}} = \frac{\sum_{g \in \mathcal{J}^{\mathrm{CN}}_{(-f)j,12}} \mathrm{Sale}_{gj,12} - \sum_{g \in \mathcal{J}^{\mathrm{CN}}_{(-f)j,99}} \mathrm{Sale}_{gj,99}}{\mathrm{Total\ sales}_{j,98}}, \tag{3.4}$$

where $\mathcal{J}^{\mathrm{CN}}_{(-f)jt}$ is a set of sector $j$ FDI affiliates in China in year $t$.[18] To rule out mechanical correlations, we exclude any FDI affiliates related to firm $f$ in the numerator, denoted as $-f$. If $f$ is a Chinese partner, we exclude all JV affiliates in which $f$ holds ownership. If $f$ is a JV affiliate, we exclude all JV affiliates

[18] This is a standard sectoral FDI exposure measure in the literature (e.g. Aitken and Harrison, 1999; Blalock and Gertler, 2008; Lu et al., 2017; Jiang et al., 2023)).

that share the same Chinese parents. One issue is the concordance between CIC and SIC codes, as a single 4-digit CIC code often maps to multiple SIC 4-digit codes. Therefore, we first construct the sectoral shock at the SIC 4-digit level, as most datasets are in SIC codes. Then, for CIC codes with multiple SIC mappings, we take a weighted average. Appendix Section B.1 provides further details.

To isolate effects of the FDI exposure from changes in trade policies post-WTO, we include $\text{NTRgap}_j$ that measures reductions in trade policy uncertainty between the US and China due to the granting of Permanent Normal Trade Relations (PNTR) (Pierce and Schott, 2016), defined as the increase in US tariffs on Chinese goods in case of a failed annual renewal of China's Normal Trade Relations (NTR) status prior to granting the PNTR.[19]

**IV Strategy.** The naive OLS estimates can be biased due to endogeneity as unobservable factors may affect both FDI flows and firm growth simultaneously. For example, pull factors of FDI flows into China include positive demand and productivity shocks in China, while the push factors from the US include rising labor costs. These pull and push factors are likely to affect firm growth in both countries. Reductions in unobservable bilateral trade costs between the two countries can also be a source of endogeneity, as MNEs may enter China to serve the large US market.[20] The direction of the bias is ambiguous. Unobserved positive demand shocks in China could drive both higher US FDI flows into China and faster Chinese firm growth, leading to an upward bias. Conversely, increased FDI may intensify competition within China, negatively affecting Chinese firm growth and resulting in a downward bias. Measurement error in the FDI exposure is another potential source for a downward bias.

To address endogeneity, we use an IV strategy similar to Autor et al. (2013). The IV is constructed as the ratio of the total sales of JV in India affiliated with MNEs from Japan or South Korea, relative to China's total sector sales in 1998:

$$\text{IV}_j = \frac{\Delta\text{India FDI (Japan and S. Korea) sales}_{jt}}{\text{Total sales}^{\text{CN}}_{j,98}} = \frac{\sum_{g \in \mathcal{J}^{\text{IN,JP-KR}}_{j,12}} \text{Sale}_{gj,12} - \sum_{g \in \mathcal{J}^{\text{IN,JP-KR}}_{j,99}} \text{Sale}_{gj,99}}{\text{Total sales}^{\text{CN}}_{j,98}}, \quad (3.5)$$

$\mathcal{J}^{\text{IN,JP-KR}}_{jt}$ is the set of FDI affiliates in India associated with MNEs from Japan or South Korea. We obtain data on Indian firm balance sheets and ownership from the Prowess database, supplemented with the ownership information from Orbis. The dataset covers over 70% of the Indian manufacturing sector and is representative of large and medium-sized firms. While it may exclude some small firms, this is unlikely to be a major concern, as we focus only on the sales of FDI affiliates in India, which are

[19] We obtain the SIC 4-digit level NTR gap from Che et al. (2022). $\text{NTRgap}_j$ is computed for each four-digit SIC code based on ad valorem equivalent tariff rates for 1999: $\text{NTRgap}_j = \text{Non NTR Rate}_{j,99} - \text{NTR Rate}_{j,99}$. It has been well-documented in the trade literature that such reductions measured by the NTR gap contributed to declines in US manufacturing (e.g. Pierce and Schott, 2016; Handley and Limão, 2017).

[20] For example, McCaig et al. (2023) find that after the US-Vietnam Bilateral Trade Agreement, which reduced US import tariffs on exports from Vietnam, employment grew faster in more exposed industries, primarily driven by the entry of new foreign affiliates of MNEs.

typically larger than domestic Indian firms.[21]

The idea behind the IV is as follows. The IV strategy aims to isolate variation in China's FDI exposure that is plausibly exogenous to factors specific to the US and China. For example, consider exogenous productivity shocks in Japan or South Korea that increase overall FDI by those two countries. By using their FDI affiliates in India in the IV, the IV extracts these exogenous shocks. The explicit identifying assumption is that any unobservables that affect US FDI in China are uncorrelated with the IV. We choose India for its attractiveness to FDI due to its large market size, low wages, and strong economic growth potential, a condition similar to China's as reflected in the term BRICS.[22] Moreover, Japan and South Korea were the two largest sources of FDI in China. Appendix Figure B4 presents a binscatter plot of the first-stage relationship at the SIC 4-digit level, showing a significantly positive relationship between the FDI exposure and IV.[23]

**Threats to identification.** Before presenting the estimation results, we discuss two main potential threats to identification: export platform and technological changes.[24] First, regarding export platform, demand shocks in China may induce South Korean and Japanese MNEs to invest in India to serve the Chinese market, and vice versa. Similarly, US demand shocks may cause South Korean and Japanese MNEs to invest in China or India to serve the US market. In both cases, the exclusion restriction is violated because both demand shocks influence FDI flows into India from the two countries. The second concern is technological changes that are skill-biased (e.g. Acemoglu et al., 2015; Aum et al., 2018; Aum and Shin, 2025) or reduce communication costs between headquarters and affiliates (e.g. Keller and Yeaple, 2013; Fort, 2017). These shocks may make certain sectors more attractive for FDI, potentially correlating FDI by MNEs in the US, Japan, or South Korea.

We investigate these concerns by inspecting pre-trends and industry-level balance, following Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020), reported in Appendix Table B5. First, we find that pre-1999 5 year growth (1993-1998) in industry-level variables are not meaningfully correlated with the IV. Overall imports (excluding China, India, Japan, and South Korea), and imports from China do not show any pre-trends. Although the IV has weak positive correlations with gross output and employment at the 10% significance level, these relationships are in the opposite direction with the negative competition effects on US firms. We also find no significant correlation with the pre-1999 5-year growth of US firm-level variables (Appendix Table B6).[25]

We assess industry-level balance by checking the correlation between our IV and initial sectoral

[21] Goldberg et al. (2010) provide a more detailed discussion of the data.

[22] The term BRICS refers to a group of emerging economies with high growth potential, including Brazil, Russia, India, China, and South Africa.

[23] The estimated linear-fit coefficient is 9.4, with a $t$-statistic of 4.9 and an adjusted R-squared of 0.22. The magnitude aligns with the fact that China's total FDI inflows were approximately 10 times larger than India's. The most exposed industries to FDI were machinery and motor vehicle-related sectors.

[24] Another potential concern is that globalization trends in liberalization of trade and FDI could make policy reforms in China and India be correlated. However, this is unlikely, as India's major trade and FDI reforms were implemented in 1991, with WTO accession in 1995, about 6 years before China (Sivadasan, 2009; Goldberg et al., 2010). By taking differences between 1999 and 2012, the IV effectively removes the effects of India's reforms, which had already been in place by 1999.

[25] Since Chinese firm data is only available after 1998, so we are unable to assess their pre-trends.

characteristics that could be related to unobserved shocks. The export platform is unlikely to be a significant concern, as there is no significant correlations between bilateral import penetration (import-to-domestic absorption ratio) and the IV for China, India, and the US. Moreover, sectors with higher IVs are not necessarily those in which China initially had higher productivity or those more exposed to FDI, supported by the lack of correlation between the IV and Chinese import penetration in the US, FDI affiliates' initial sales shares in China, or their numbers relative to the total firm numbers. While our research design does not require sectors to be identical in levels, no correlations with these variables support the plausibility of the exclusion restriction.

Three variables related to technological change are significantly correlated with the IV: overall US import penetration (excluding China, India, Japan, and South Korea), production workers' employment shares, and computer investment share. This raises concerns for omitted variable bias from unobservable technological changes especially in labor-intensive sectors that are often characterized by higher foreign import penetration, larger production worker shares, and lower computer investment. However, if such unobservables were driving our results, they would likely appear as negative pre-trends in gross output or employment, which we do not observe. Also, including them as additional controls leaves our estimates essentially unchanged. Consequently, such bias as unlikely to a big concern.

**Estimation results.** Table 1 presents the results. In column 1, the dependent variable is sales growth. Both OLS and IV estimates are positive and statistically significant at the 1% level, with the strong first-stage. The IV estimate has a larger magnitude than the OLS estimate, indicating that a 1 percentage point increase in the FDI exposure led to an 8.97 percentage point increase in sales growth. In column 2, we include three additional variables that showed significant correlations with the IV in the balance test (see Appendix Table B5) and 1-digit industry dummies. The coefficients remain stable within one standard error of the estimate without the controls. In columns 3-8, the FDI exposure also had positive effects on the DHS growth rates of capital, employment, and exports.[26] The NTR gap had positive effects on Chinese firms, although these estimates are less precise. Overall, the OLS estimates are downward biased, likely due to measurement errors in the FDI exposure, but this bias falls within one standard error of the IV estimates.

**Evidence of quality/productivity upgrading.** We further provide evidence that these Chinese firms' improvements were associated with their quality/productivity upgrading, reported in Table 2. In columns 1-2, the outcomes are DHS growth of cumulative patents and wages per employment (a proxy for workers' skills). Since 2008, the Chinese government implemented a "high-tech" certification policy, granting tax credits to firms meeting standards for intellectual property and R&D. We use a dummy of whether firms ever received the "high-tech" status between 2008 and 2024 as as an outcome

[26] The sample size decreases for export outcomes in columns 7-8, as for DHS growth to be well-defined, firms must have at least one non-zero value for the outcome at the start or end of the sample period.

Table 1: Indirect Positive Spillovers to Chinese Firms

| Dep. var. | ΔSale | | ΔEmp. | | ΔCapital | | ΔExport | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | *Panel A. OLS* | | | | | | | |
| $\Delta \text{FDI}_{fj}$ | 8.97*** | 7.47*** | 7.30*** | 7.25*** | 8.89*** | 7.19*** | 19.91*** | 16.71*** |
| | (1.73) | (2.03) | (1.40) | (1.56) | (1.79) | (1.84) | (3.37) | (3.01) |
| $\text{NTRgap}_j$ | −0.08 | 0.10 | 0.55* | 0.65** | 0.15 | 0.18 | 1.28* | 1.07* |
| | (0.32) | (0.34) | (0.29) | (0.27) | (0.29) | (0.29) | (0.73) | (0.65) |
| | *Panel B. IV* | | | | | | | |
| $\Delta \text{FDI}_{fj}$ | 12.16*** | 8.98*** | 10.31*** | 10.89*** | 12.40*** | 10.04*** | 23.77*** | 19.60*** |
| | (3.34) | (2.92) | (2.34) | (2.16) | (3.05) | (2.77) | (5.37) | (4.29) |
| $\text{NTRgap}_j$ | 0.03 | 0.15 | 0.65** | 0.78*** | 0.27 | 0.28 | 1.45* | 1.20* |
| | (0.32) | (0.35) | (0.29) | (0.27) | (0.28) | (0.29) | (0.76) | (0.67) |
| KP-*F* | 45.75 | 42.22 | 45.75 | 42.22 | 45.75 | 42.22 | 45.37 | 41.85 |
| Add. ctrl. | | ✓ | | ✓ | | ✓ | | ✓ |
| Mean dep. var. | 79.61 | 79.61 | −7.08 | −7.08 | 38.83 | 38.83 | 50.60 | 50.60 |
| # clusters | 157 | 157 | 157 | 157 | 157 | 157 | 155 | 155 |
| N | 14,844 | 14,844 | 14,844 | 14,844 | 14,844 | 14,844 | 8,491 | 8,491 |

**Notes:** Standard errors, clustered at the CIC-3 digit levels, are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.3). $\Delta \text{FDI}_{fj}$ and the IV are defined in equations (3.4) and (3.5). In columns 1-2, 3-4, and 5-6, the dependent variables are the DHS growth rates of sales, employment, capital, and exports of Chinese firms. The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. All specifications include dummies of state-owned firms and FDI affiliates, and province fixed effects. The even columns include 1996 US import penetration (overall imports, excluding US, China, India, Japan, and South Korea, relative to domestic absorption), 1993 production worker shares, 1990 computer investment shares, and 1-digit industry dummies. KP-*F* is the Kleibergen-Papp F-Statistics. All regression models are weighted by initial sales.

in column 3.[27] In columns 4-7, the outcomes are DHS growth of the number of exporting/importing products/countries between 2000 and 2013, obtained from the Chinese customs data, which have been well-documented to be positively correlated with firm-level quality/productivity (e.g. Manova and Zhang, 2012).[28] It have been well-documented that these variables have positive relationships with firm-level quality/productivity in the international trade literature (e.g. Manova and Zhang, 2012).

There are several potential channels behind these indirect spillovers. First, the results may reflect knowledge diffusion from MNEs to other firms, such as through labor mobility. In fact, in Appendix Section B.2, we provide additional evidence supporting knowledge diffusion using citation flows, a commonly used proxy for knowledge flows. We find that foreign MNEs that formed JVs began to

[27] We obtain information on whether firms received the high-tech status from the Ministry of Industry and Information Technology. The policy requires firms to obtain the ownership of the intellectual property rights that play a core supporting role in the technology of its main products (services) through independent research and development, assignment, donation, and merger and acquisition.

[28] Changes are measured from 2000 to 2013 due to data unavailability for years of 1999 and 2012 in the customs data.

Table 2: Evidence of Quality Upgrading of Chinese Firms

| Dep. var. | Δ cumulative patent | ΔWage per emp | Dum gvnt high-tech | Δ # export prod | Δ # export cty | Δ # import prod | Δ # import cty |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\Delta\text{FDI}_{fj}$ | 3.09** | 2.51*** | 4.36*** | 25.25*** | 23.09*** | 10.55*** | 13.65*** |
| | (1.43) | (0.83) | (1.41) | (2.88) | (3.18) | (3.65) | (3.22) |
| $\text{NTRgap}_j$ | 0.58* | 0.02 | 0.13 | 1.81*** | 1.55*** | 1.95*** | 1.91*** |
| | (0.30) | (0.16) | (0.11) | (0.43) | (0.41) | (0.36) | (0.40) |
| KP-*F* | 60.98 | 45.14 | 45.75 | 31.29 | 31.30 | 35.41 | 35.41 |
| Mean dep. var. | 172.28 | 120.54 | 18.97 | 36.30 | 33.77 | −24.95 | −7.21 |
| # clusters | 157 | 157 | 157 | 153 | 153 | 154 | 154 |
| N | 6,628 | 14,817 | 14,844 | 7,316 | 7,312 | 6,414 | 6,410 |

**Notes:** Standard errors, clustered at the CIC-3 digit levels, are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the IV estimate of equation (3.3). $\Delta\text{FDI}_{fj}$ and the IV are defined in equations (3.4) and (3.5). In columns 1-7, the dependent variables are the DHS growth of cumulative patents and wages per employment, dummies for firms receiving high-tech status from the Chinese government in 2024, and the DHS growth of the numbers of exporting/importing products/countries between 2000-2013. The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. All specifications include dummies of state-owned firms and FDI affiliates, and province fixed effects. KP-*F* is the Kleibergen-Papp F-Statistics. All regression models are weighted by initial sales.

receive more citations from non-partner Chinese firms (Appendix Figure B1). Second, FDI affiliates are likely to generate greater demand and lower supply costs for other Chinese firms (e.g. Alfaro-Ureña et al., 2022), thus providing stronger incentives for quality and productivity upgrading. Setzler and Tintelnot (2021) also find similar positive indirect spillovers of FDI in the US.

### Fact 3. Indirect Negative Competition Effects to US Firms

In this subsection, we examine the indirect negative competition effects to US firms. We show that FDI played a key role in driving China's export growth and the decline of US manufacturing. We run the following long-difference regression at the sector level for 1999-2012 using the same IV strategy:

$$\Delta y_j = \beta \Delta\text{FDI}_{fj} + \text{NTRgap}_j + \varepsilon_{fj}, \tag{3.6}$$

where $j$ denotes 4-digit SIC industry. The dependent variables $\Delta y_{fj}$ are DHS growth rates of sector $j$'s outcomes. Regression models are weighted by initial gross output. Standard errors are clustered at the SIC-3 digit level.

Table 3 presents the results. Both OLS and IV estimates indicate that US imports from China grew faster in sectors more exposed to FDI (col 1). The IV estimate implies that a one percentage point increase in the FDI exposure raised US imports by an 8.3 percentage point. Similarly, imports from China to other countries show the same pattern as US imports (col 2).[29] One concern is that the

[29] These countries, including Australia, Denmark, Finland, Germany, New Zealand, Spain, and Switzerland, are selected based on Autor et al. (2013), excluding Japan, which is used in the IV construction.

Table 3: Sectors with Higher FDI Exposure Experienced Larger Chinese Export Growth and Greater Declines in US Manufacturing

| Dep. | ΔUS-CN import | ΔOC-CN import | ΔUS-CN import (ex. FDI) | ΔOC-CN import (ex. FDI) | ΔGross output | ΔEmp. | ΔPPI |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | *Panel A. OLS* | | | | | | |
| $\Delta FDI_j$ | 6.08** | 7.47** | 7.02*** | 4.95*** | −2.88 | −0.51 | −8.52** |
| | (2.35) | (2.91) | (1.20) | (1.07) | (2.39) | (1.61) | (3.46) |
| $NTRgap_j$ | 0.22 | 0.21 | 0.55* | 0.29 | −1.42*** | −0.94*** | −1.66*** |
| | (0.30) | (0.33) | (0.28) | (0.23) | (0.43) | (0.19) | (0.51) |
| | *Panel B. IV* | | | | | | |
| $\Delta FDI_j$ | 8.30*** | 10.39*** | 10.63*** | 10.19*** | −5.65** | −2.80** | −10.81*** |
| | (1.97) | (2.71) | (1.79) | (1.71) | (2.53) | (1.37) | (3.63) |
| $NTRgap_j$ | 0.29 | 0.30 | 0.63* | 0.46 | −1.50*** | −1.01*** | −1.73*** |
| | (0.35) | (0.37) | (0.35) | (0.30) | (0.41) | (0.19) | (0.48) |
| KP-*F* | 67.97 | 67.97 | 67.97 | 67.97 | 67.97 | 67.97 | 67.97 |
| Mean dep. var. | 136.68 | 146.98 | 141.41 | 153.95 | 14.37 | −40.05 | 26.94 |
| # clusters | 130 | 130 | 130 | 130 | 130 | 130 | 130 |
| N | 383 | 383 | 383 | 383 | 383 | 383 | 383 |

**Notes:** Standard errors clustered at the SIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.6). $\Delta FDI_j$ is the FDI exposure defined in equation (3.4) and the IV is defined in equation (3.5). The dependent variables are DHS growth rates for US imports from China between 1999-2012 (column 1), imports from China by selected countries between 1999-2012 (column 2), US and other countries' imports from China excluding FDI subsidiaries between 2000-2013 (columns 3 and 4), obtained from the customs data, and US sectoral gross output, employment, and producer price index between 1999-2012 (columns 5-7). The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. KP-*F* is the Kleibergen-Papp F-Statistics. All regression models are weighted by initial gross output.

observed import growth may reflect both offshoring effects and gains among Chinese firms through direct and indirect spillovers in Facts 1 and 2. To separate the former from the latter channel, we compute import flows, excluding FDI subsidiaries (both JVs and WOFEs) using the Chinese customs data.[30] By excluding all FDI subsidiaries, these import flows do not reflect offshoring effects. The similar coefficient magnitudes in columns 3-4 shows the importance of the spillover channel.[31]

Also, sectors more exposed to FDI experienced larger declines in gross output, employment, and producer price indices (PPI) (cols. 5-7), consistent with increased competitive pressures from Chinese firms.[32] A one standard deviation increase in the NTR gap decreased gross output by 23.4 percentage

[30]The Chinese customs data has information on whether exporters or importers are FDI subsidiaries or not. Because Chinese customs data covers the period between 2000 and 2013, we use the growth rate between 2000 and 20123, unlike the other variables with growth rates defined over periods between 1999 and 2012. Total exports to the US by Chinese FDI subsidiaries accounted for approximately 42% of all Chinese exports to the US.

[31]Consistent with the sectoral results, we re-estimate equation (3.3) on a sample that excludes all FDI subsidiaries. As shown in columns 1-2 of Appendix Table B9, the export effects remain positive and significant.

[32]The declines in PPI are consistent with Amiti et al. (2020) and Jaravel and Sager (2019) who also find that increased China's export lowered US price levels.

points ($1.50 \times 15.6$), whereas the same increase in the FDI exposure reduced it by 12.9 percentage points ($5.6 \times 2.3$). Roughly speaking, the FDI exposure's effect was 55% of the NTR gap's effect.

Next, we examine the indirect negative competition effects at the firm level. We estimate the same regression model for Chinese firms, but with US firm outcomes as the dependent variables. In contrast to Chinese firms, we expect the coefficients of the FDI exposure to be negative, as the gains of Chinese firms from FDI would increase competitive pressures in the global market. When constructing the FDI exposure, for each US MNE, Chinese FDI affiliates associated with it are excluded from the numerator.[33]

Table 4 reports the results. Column 1 reports the OLS and IV estimates for sales growth. Both estimates are significantly negative at the 1% level. The IV estimate implies that a one percentage point increase in the FDI exposure led to a 16.1 percentage point decline in sales growth. The result remains stable with the additional controls in column 2. The FDI exposure also had negative effects on employment, capital, and export growth (cols. 3-8), aligning with the sectoral evidence. The FDI exposure also had negative impacts on US firms' innovation outcomes including R&D and the number of new patents (cols. 9-12), which are consistent with Autor et al. (2020) who found the negative impacts of the China shock on US firms' innovation outcomes.

We conduct a battery of robustness checks for firm- and sector-level results in facts 2 and 3. The knowledge spillovers are further supported by the fact that the indirect effects were larger for more R&D-intensive sectors (Appendix Table B8). We show that the FDI exposure not only negatively affected US firms but also firms in other countries (Appendix Table B7), further supporting the increased global competition. Also, our results remain robust to alternative clustering at the 4-digit industry level, an alternative sample period between 1999 and 2007 (before the Great Recession), an alternative FDI exposure measure based on domestic sales instead of total sales (removing export components), and an alternative IV solely based on Japan's FDI. The results remain robust to including China's FDI policy changes as additional controls.[34] Finally, the fact 3 firm-level results are robust to restricting the regression sample to US firms that never had FDI in China. These results are reported in Appendix Tables B9, B10, and B11.

# 4. Theoretical Framework

In this section, we develop a two-country growth model with oligopolistic competition and endogenous innovation and joint venture decisions, capturing the three empirical facts documented in the previous section.

[33] By excluding own FDI affiliates associated with each US MNE, the negative coefficients do not reflect the substitution of domestic production and employment with foreign affiliates within MNEs (e.g., Muendler and Becker, 2010; Boehm et al., 2020; Lin et al., 2024).

[34] We include changes in sector-level dummies for being subject the FDI regulation based on the Catalogue for the Guidance of Foreign Investment Industries over 1998-2007 (Lu et al., 2017; Eppinger and Ma, 2024), and changes in log import/output tariffs. The data for these additional controls are obtained from Brandt et al. (2017).

Table 4: Indirect Negative Competition Effects to US Firms

| Dep. | $\Delta$Sale | | $\Delta$Emp. | | $\Delta$Capital | | $\Delta$Export | | $\Delta$R&D | | $\Delta$Patent | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | *Panel A. OLS* | | | | | | | | | | | |
| $\Delta FDI_{fj}$ | $-11.08^{***}$ | $-9.32^{***}$ | $-10.65^{***}$ | $-7.95^{***}$ | $-12.90^{***}$ | $-9.31^{***}$ | $-7.97^{*}$ | $-6.74^{*}$ | $-10.53^{**}$ | $-6.57^{**}$ | $-0.34$ | $-0.93$ |
| | (2.95) | (1.81) | (3.33) | (2.31) | (2.76) | (2.63) | (4.21) | (3.45) | (4.25) | (2.97) | (1.53) | (1.79) |
| $NTRgap_j$ | $-1.10$ | $-1.14^{*}$ | $-1.01$ | $-1.24^{*}$ | $-0.87$ | $-1.04$ | $-1.49$ | $-1.38$ | $-1.45$ | $-1.48^{**}$ | $0.67^{*}$ | 0.48 |
| | (0.78) | (0.63) | (0.91) | (0.71) | (0.89) | (0.69) | (1.37) | (1.30) | (0.89) | (0.69) | (0.40) | (0.34) |
| | *Panel B. IV* | | | | | | | | | | | |
| $\Delta FDI_{fj}$ | $-17.68^{***}$ | $-14.09^{***}$ | $-18.28^{***}$ | $-12.02^{***}$ | $-22.42^{***}$ | $-16.28^{***}$ | $-14.70^{**}$ | $-13.04^{*}$ | $-18.86^{***}$ | $-11.53^{*}$ | $-3.53^{*}$ | $-4.30^{**}$ |
| | (3.74) | (3.64) | (4.40) | (3.83) | (4.02) | (4.22) | (6.19) | (7.28) | (5.31) | (6.53) | (1.98) | (2.01) |
| $NTRgap_j$ | $-1.61^{*}$ | $-1.36^{*}$ | $-1.60$ | $-1.43^{*}$ | $-1.61$ | $-1.38^{*}$ | $-2.05$ | $-1.70$ | $-2.22^{*}$ | $-1.74^{**}$ | 0.41 | 0.32 |
| | (0.94) | (0.73) | (1.11) | (0.80) | (1.02) | (0.76) | (1.66) | (1.47) | (1.12) | (0.81) | (0.37) | (0.25) |
| KP-*F* | 138.67 | 197.69 | 138.67 | 197.69 | 138.67 | 197.69 | 123.69 | 188.18 | 80.15 | 139.99 | 121.27 | 187.33 |
| Controls | | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | | ✓ |
| Mean dep. var. | 8.69 | 8.69 | −10.82 | −10.82 | 0.52 | 0.52 | 35.91 | 35.91 | 6.33 | 6.33 | 62.76 | 62.76 |
| # clusters | 105 | 105 | 105 | 105 | 105 | 105 | 101 | 101 | 80 | 80 | 100 | 100 |
| N | 1,017 | 1,017 | 1,017 | 1,017 | 1,017 | 1,017 | 834 | 834 | 525 | 525 | 840 | 840 |

**Notes:** Standard errors clustered at the SIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.3). The FDI exposure $\Delta FDI_{fj}$ and the IV are defined in equations (3.4) and (3.5), respectively. In columns 1-2, 3-4, 5-6, 7-8, 9-10, and 11-12, the dependent variables are DHS growth of US firms' sales, employment, capital, exports, R&D, and cumulative patents between 1999-2012, respectively. The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. The even columns include 1996 US import penetration (overall imports, excluding US, China, India, Japan, and South Korea, relative to domestic absorption), 1993 production worker shares, 1990 computer investment shares, and 1-digit industry dummies. KP-*F* is the Kleibergen-Papp F-Statistics. All regression models are weighted by initial sales.

## 4.1 Setup

The world consists of two large countries, Home and Foreign $c \in \{H, F\}$, corresponding to the US and China. Time is continuous, $t \in [0, \infty)$. There are two sectors, tradable and non-tradable. The tradable sector comprises a unit mass continuum of products $j \in [0, 1]$, with each firm producing a unique variety within products. Each variety is tradable across countries, subject to iceberg trade costs $\tau^x \geq 1$—a firm needs to ship $\tau^x$ units of varieties to export one unit. Each country has a representative household, immobile across countries, that owns all domestic firms and supplies labor inelastically. There is no trade in assets, ruling out international borrowing and lending.

There are three types of firms: leaders, fringe firms, and JVs. JVs can be established through mutual agreements between leaders from both countries. We assume that only Home leaders form JVs in Foreign (and not vice versa), so the set of operating firms in Foreign varies by products and over time, while Home's firm composition remains fixed. Sets of firm for product $j$ at time $t$ are $\mathcal{I}_H = \{h, \tilde{h}\}$ for Home and $\mathcal{I}_{Fjt} = \{f, \tilde{f}, v\}$ for Foreign, where $h$ and $f$ are leaders, $\tilde{h}$ and $\tilde{f}$ are fringe firms, and $v$ is a JV.

## 4.2 Household

A representative household in Home maximize Cobb-Douglas utility,

$$U_{Ht} = \int_t^\infty \exp\big(-\rho(s-t)\big) \ln C_{Hs} ds\,, \qquad \text{s.t.} \qquad r_{Ht}A_{Ht} + w_{Ht}L_H = P_{Ht}C_{Ht} + T_{Ht} + \dot{A}_{Ht}\,, \tag{4.1}$$

where $C_{Hs}$ is final consumption good (price index $P_{Ht}$), $\rho > 0$ is the discount factor, $r_{Ht}$ is interest rate, $L_H$ is labor endowment, and $w_{Ht}$ is wage. $T_{Ht}$ is lump-sum transfer from the government, $A_{Ht}$ is assets owned by households, and $\dot{A}_{Ht}$ is time derivative of $A_{Ht}$. Its Euler equation is given by

$$\frac{\dot{C}_{Ht}}{C_{Ht}} = r_{Ht} - \left(\rho - \frac{\dot{P}_{Ht}}{P_{Ht}}\right).$$

## 4.3 Sectors

A final consumption good is produced using a Cobb-Douglas aggregator, which combines outputs from the tradable and non-tradable sectors ($C^T_{Ht}$ and $C^N_{Ht}$):

$$C_{Ht} = (C^T_{Ht})^\beta (C^N_{Ht})^{1-\beta}, \qquad P_{Ht} = \left(\frac{P^T_{Ht}}{\beta}\right)^\beta \left(\frac{P^N_{Ht}}{1-\beta}\right)^{1-\beta}$$

where $\beta$ denotes the expenditure share on the tradable sector, and $P^T_{Ht}$ and $P^N_{Ht}$ denote the price indices of tradable and non-tradable sectoral outputs, respectively.

A sectoral good in the non-tradable sector is produced by a perfectly-competitive representative firm as follows:

$$C_{Ht}^N = Z_{Ht}^N L_{Ht}^N,$$

where $Z_{Ht}^N$ is exogenous productivity of the non-tradable sector, which grows at rate $g^{NT}$. With perfect competition, $P_{Ht}^N = \frac{w_{Ht}}{Z_{Ht}^N}$.

The tradable sectoral output is produced by aggregating varieties produced by Home and Foreign firms across products:

$$C_{Ht}^T = \exp\left(\int_0^1 \ln\left(\mathcal{I}_{jt}^{-\frac{1}{\sigma}}\left(\sum_{i\in\mathcal{I}_H}\psi_i^{\frac{1}{\sigma}} y_{ijt}^{\frac{\sigma-1}{\sigma}} + \sum_{i\in\mathcal{I}_{Fjt}}\psi_i^{\frac{1}{\sigma}}(y_{ijt}^*)^{\frac{\sigma-1}{\sigma}}\right)\right)^{\frac{\sigma}{\sigma-1}} \mathrm{d}j\right),$$

where $y_{ijt}$ and $y_{ijt}^*$ are the quantities of varieties produced by domestic and foreign firms for product $j$, with the superscript "$*$" indicating exported varieties. $\psi_i$ is a demand shifter for each firm. Leaders in both countries and the JV have the same parameter value ($\psi = \psi_h = \psi_f = \psi_v$), while fringe firms have a different common value ($\tilde{\psi} = \psi_{\tilde{h}} = \psi_{\tilde{f}}$), which are normalized such that $\psi + \tilde{\psi} = 1$. Varieties are imperfectly substitutable within products, with the elasticity of substitution $\sigma \in (1, \infty)$. Because we do not want introducing a new variety by forming a JV to mechanically increase utility, we neutralize love of variety by normalizing the sectoral output with the sum of all firms' demand shifters $\sum_{i\in\mathcal{I}_{jt}}\psi_i$, where $\mathcal{I}_{jt} = |\mathcal{I}_H \bigcup \mathcal{I}_{Fjt}|$. The corresponding price index is

$$P_{Ht}^T = \exp\left(\int_0^1 \left(\frac{1}{\sum_{i\in\mathcal{I}_{jt}}\psi_i}\left(\sum_{i\in\mathcal{I}_H}\psi_i p_{ijt}^{1-\sigma} + \sum_{i\in\mathcal{I}_{Fjt}}\psi_i (p_{ijt}^*)^{1-\sigma}\right)\right)^{\frac{1}{1-\sigma}} \mathrm{d}j\right),$$

where $p_{ijt}$ and $p_{ijt}^*$ are prices charged by domestic and foreign firms.

### 4.4 Firms

**Production and market structure.** A firm's production function is linear in labor: $\mathcal{Y}_{ijt} = z_{ijt} l_{ijt}$, where $z_{ijt}$ denotes productivity and $l_{ijt}$ labor inputs. Because its output can be sold in both markets, it is subject to the resource constraint: $\mathcal{Y}_{ijt} = y_{ijt} + \tau^x y_{ijt}^*$.

Leaders or JVs engage in Bertrand competition, charging variable markups over their marginal costs. With the CES aggregator, their markups become a function of their market shares (Atkeson and Burstein, 2008). Home leaders' prices in Home and Foreign markets are given by

$$p_{hjt} = \frac{1 - \frac{\sigma-1}{\sigma}s_{hjt}}{\frac{\sigma-1}{\sigma}(1 - s_{hjt})}\frac{w_{Ht}}{z_{hjt}} \qquad \text{and} \qquad p_{hjt}^* = \frac{1 - \frac{\sigma-1}{\sigma}s_{hjt}^*}{\frac{\sigma-1}{\sigma}(1 - s_{hjt}^*)}\frac{\tau^x w_{Ht}}{z_{hjt}}, \tag{4.2}$$

where $s_{hjt}$ and $s_{hjt}^*$ are their market shares in Home and Foreign, respectively. Their operating profits in Home and Foreign are given by

$$\pi_{hjt} = \frac{s_{hjt}}{\sigma - (\sigma-1)s_{hjt}} P^T_{Ht} C^T_{Ht} \qquad \text{and} \qquad \pi^*_{hjt} = \frac{s^*_{hjt}}{\sigma - (\sigma-1)s^*_{hjt}} P^T_{Ft} C^T_{Ft}. \tag{4.3}$$

The total operating profits is the sum in both markets: $\Pi_{hjt} = \pi_{hjt} + \pi^*_{hjt}$.

Unlike the other types of firms, fringe firms charge monopolistically competitive constant markups. Their prices are $p_{\tilde{h}jt} = \frac{\sigma}{\sigma-1}\frac{w_{Ht}}{z_{\tilde{h}jt}}$ and $p^*_{\tilde{h}jt} = \frac{\sigma}{\sigma-1}\frac{\tau^x w_{Ht}}{z_{\tilde{h}jt}}$ and their operating profits are $\pi_{\tilde{h}jt} = \frac{1}{\sigma} p^{1-\sigma}_{\tilde{h}jt} P^T_{Ht} C^T_{Ht}$ and $\pi^*_{\tilde{h}jt} = \frac{1}{\sigma}(p^*_{\tilde{h}jt})^{1-\sigma} P^T_{Ht} C^T_{Ht}$. Fringe firms can be interpreted as a continuum of atomistic, homogeneous firms whose total mass is normalized to 1.

**Innovation.** Leaders can improve productivity through successive innovations. Innovations occur randomly at a Poisson rate $x_{ijt}$, with the following convex cost function:

$$h^r_{ijt} = \alpha_{cr} \frac{(x_{ijt})^\gamma}{\gamma}, \qquad \gamma > 1$$

where $h^r_{ijt}$ is R&D workers employed by firm $i$, and $\alpha_{cr}$ is a parameter that governs the scale of innovation costs in counrty $c$. Conditional on R&D investment, a firm's productivity improves with rate $x_{ijt}$ according to:

$$z_{ij,t+\Delta t} = \lambda \times z_{ijt}, \tag{4.4}$$

where $\lambda > 1$ denotes the step size of productivity improvement.

Fringe firms do not innovate, and their productivity improves only through knowledge diffusion from domestic leaders. They move up domestic leader's productivity level at rate $\delta^D$.[35]

**Joint venture.** A Home leader may collaborate with a Foreign leader to establish a JV in Foreign, which produces a new variety. The JV employs Foreign labor for production. It avoids trade costs when selling in Foreign but incurs trade costs when exporting to Home.[36] Home leaders' incentives to form a JV increase with Foreign's market size, wage differentials, and trade costs, capturing the proximity-concentration trade-off (Helpman et al., 2004).

Its productivity is given by $z_{vjt} = \frac{z_{hjt}}{\tau^z}$, where $\tau^z > 1$ represents a productivity loss associated with multinational production, as in Arkolakis et al. (2018). This loss reflects various barriers MNEs face when operating in a foreign economic and regulatory environment. The JV does not engage in innovation, but its productivity $z_{vjt}$ improves passively over time as the Home leader's productivity $z_{hjt}$ increases through innovation.[37]

[35] Previous papers have assumed similar within-country domestic diffusion (e.g. Lucas and Moll, 2014; Perla and Tonetti, 2014; König et al., 2022).

[36] Because JVs can export back to Home, our model also captures the possibility that Home leaders may use JVs as "export platforms" to serve their own markets by leveraging lower labor costs abroad (e.g., Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017; Arkolakis et al., 2018).

[37] The fact that Home leader's own innovation improves productivity of own JV aligns with Bilir and Morales (2020), who study productivity spillovers from MNE headquarters' R&D investments to foreign affiliates.

We assume that JVs maximize their own profits rather than jointly optimizing total profits with their parent firms.[38] A Home leader receives a $\kappa$ share of the JV's total profits $\Pi_{vjt}$, while the Foreign leader retains the remaining $1 - \kappa$. This assumption follows the JV Law which required MNEs and Chinese partners to share JV profits in proportion to their equity stakes.

A Home leader chooses a rate of forming a JV, $d_{hjt}$, with the following convex cost function:

$$h^d_{hjt} = \alpha_{Hd} \frac{(d_{hjt})^\gamma}{\gamma}, \qquad \gamma > 1,$$

where $\alpha_{Hd}$ governs the scale of the cost, and $h^d_{hjt}$ represents the labor employed for JV establishment. We assume that JV costs have the same curvature parameter as innovation costs due to the lack of information on the costs of setting up JVs.[39] $h^d_{hjt}$ captures expenses for training local managers or legal processing costs associated with setting up a new firm.

With successful rate of $d_{hjt}$, Home and Foreign leaders enter Nash bargaining, which determines the one-time fee $C_{jt}$ that the Home leader pays or receives, which will be detailed in the next subsection. This fee ensures mutual gains for both Home and Foreign leaders, with the surplus shared according to their respective bargaining powers.[40]

Once established, a JV operates until it exits exogenously at rate $\chi$. While operating, the lagging partner (Home or Foreign) directly learns from its more advanced partner, catching up to that partner's productivity at rate $\phi$, capturing the fact 1. JVs also indirectly benefit Foreign fringe firms through within-country diffusion, as in the fact 2. These direct and indirect productivity gains of Chinese firms, combined with heightened competition from US leaders' JVs, reduce US fringe firms' profits, consistent with the fact 3.

### 4.5 Equilibrium

In this section, we define a Markov Perfect Equilibrium of the model, where firms' strategies depend on payoff-relevant state variables.

**State variable.** Let $N_{ijt}$ be the number of past innovations. Then, technology gaps between Home and Foreign leaders can be expressed as

$$\frac{z_{hjt}}{z_{fjt}} = \frac{\lambda^{N_{hjt}}}{\lambda^{N_{fjt}}} = \lambda^{m^F_{jt}}. \tag{4.5}$$

[38] This can be microfounded through the agency problem, where the manager of the JV maximizes only the profit of the JV it is managing, rather than the total profits in conjunction with its parent firms.

[39] In principle, we could allow for two different parameter values for these curvatures. To estimate or calibrate the JV cost curvature, we would require information on the costs of setting up a JV, which is rarely available in the data.

[40] This one-time fee can be viewed as a generalization of fixed/sunk costs, typically assumed in the FDI literature. The amounts of these sunk costs and the party (Home or Foreign leaders) that bears these costs are determined endogenously through Nash bargaining between Home and Foreign leaders, based on technology gaps. Because Home leaders establish JVs only when their additional profits exceed the one-time fee, and because JV formation is probabilistic nature, our model accounts for the extensive margin of JVs as observed in the data.

$m^F_{jt} \equiv N_{hjt} - N_{fjt} \in \{-\bar{m}, \ldots, 0, \ldots, \bar{m}\}$ is size of the technology gap. $m^F_{jt} > 0$ implies that Home leader has higher productivity than Foreign leader. $\bar{m}$ and $-\bar{m}$ are large but exogenously given upper and lower bounds of the gap, which makes the state space finite and computation feasible. Similarly, technology gaps between leader and fringe firms in Home and Foreign are

$$\frac{z_{hjt}}{z_{\tilde{h}jt}} = \lambda^{m^{DH}_{jt}}, \qquad \frac{z_{fjt}}{z_{\tilde{f}jt}} = \lambda^{m^{DF}_{jt}}.$$

$\mathbf{m}_{jt} = \{m^F_{jt}, m^{DH}_{jt}, m^{DF}_{jt}\}$ is a payoff-relevant state variable. Conditional on JV status and other aggregate variables, $\mathbf{m}_{jt}$ determines profits of each firm in each country. Because products are symmetric, we drop all subscripts of $\mathbf{m}_{jt}$ and sector-specific scripts in firm-level variables to de-clutter notations.

**Value function.** Let $V_{ht}(\mathbf{m}; \mathcal{J})$ denote the value function of Home leader $h$ given a state variable $\mathbf{m}$, with $\mathcal{J} \in \{0, 1\}$ denoting the JV status. For expositional purpose, we present only value functions of Home leaders when they are $m^F$ steps ahead of Foreign leader (i.e., $m^F > 0$ and recall $\mathbf{m} = \{m^F, m^{DH}, m^{DF}\}$). The value functions for Foreign leaders and the cases where $m^F \leq 0$ are provided in Appendix Section C.1.

The value function of a Home leader when $m^F > 0$ without JV can be expressed as follows:

$$\begin{aligned} r_{Ht} V_{ht}(\mathbf{m}; 0) - \dot{V}_{ht}(\mathbf{m}; 0) = \max_{x_{ht}, d_{ht}} \Bigg\{ & \Pi_{ht}(\mathbf{m}) - \alpha_{Hr} \frac{(x_{ht})^{\gamma}}{\gamma} w_{Ht} - \alpha_{Hd} \frac{(d_{ht})^{\gamma}}{\gamma} w_{Ht} \\ & + x_{ht}\Big(V_{ht}(\mathbf{m} + (1,1,0); 0) - V_{ht}(\mathbf{m}; 0)\Big) + x_{ft}\Big(V_{ht}(\mathbf{m} + (-1,0,1); 0) - V_{ht}(\mathbf{m}; 0)\Big) \\ & + d_{ht}\Big(V_{ht}(\mathbf{m}; 1) - V_{ht}(\mathbf{m}; 0) - C_t(\mathbf{m})\Big) \\ & + \sum_{\mathbf{m}'} \mathbb{T}(\mathbf{m}'; \mathbf{m})\Big(V_{ht}(\mathbf{m}'; 0) - V_{ht}(\mathbf{m}; 0)\Big)\Bigg\}, \end{aligned} \tag{4.6}$$

where $\mathbb{T}(\mathbf{m}'; \mathbf{m})$ denotes transition probabilities:

$$\mathbb{T}(\mathbf{m}'; \mathbf{m}) = \begin{cases} \delta^F & \text{if} \quad \mathbf{m}' = \{0, m^{DH}, m^F + m^{DF}\} \\ \delta^D & \text{if} \quad \mathbf{m}' = \{m^F, 0, m^{DF}\} \\ \delta^D & \text{if} \quad \mathbf{m}' = \{m^F, m^{DH}, 0\} \\ 0 & \text{Otherwise.} \end{cases}$$

$\delta^D$ and $\delta^F$ are Poisson rates of knowledge diffusion within and across countries. With a rate of $\delta^F$, a lagged leader catches up to the productivity with an advanced foreign leader. $\delta^F$ captures knowledge diffusion across countries through channels other than JVs.[41]

The first line of the right-hand-side in equation (4.6) represents static profits (operating profits

[41] For example, see Buera and Oberfield (2020) and de Souza et al. (2025) for knowledge diffusion through international trade.

net of innovation and JV formation costs). The second line reflects the change in values due to own innovation and a Foreign leader's innovation. The third line reflects value changes due to forming a JV. The last line reflect value changes due to exogenous spillovers.

The value function when $m^F > 0$ with JV is as follows:

$$\begin{aligned} r_{Ht} V_{ht}(\mathbf{m};1) - \dot{V}_{ht}(\mathbf{m};1) = \max_{x_{ht}} \Big\{ & \Pi_{ht}(\mathbf{m}) - \alpha_{Hr} \frac{(x_{ht})^{\gamma}}{\gamma} w_{Ht} + \kappa \Pi_{vt}(\mathbf{m}) \\ & + x_{ht}\Big(V_{ht}(\mathbf{m} + (1,1,0);1) - V_{ht}(\mathbf{m};1)\Big) + x_{ft}\Big(V_{ht}(\mathbf{m} + (-1,0,1);1) - V_{ht}(\mathbf{m};1)\Big) \\ & + \phi\Big(V_{ht}(0, m^{DH}, m^F + m^{DF};1) - V_{ht}(\mathbf{m};1)\Big) + \chi\Big(V_{ht}(\mathbf{m};0) - V_{ht}(\mathbf{m};1)\Big) \\ & + \sum_{\mathbf{m}'} \mathbb{T}(\mathbf{m}';\mathbf{m})\Big(V_{ht}(\mathbf{m}';1) - V_{ht}(\mathbf{m};1)\Big)\Big\}. \end{aligned} \tag{4.7}$$

Here, the total profit includes those generated by the JV ($\kappa\Pi_{vjt}$). Because the JV is already established, leaders no longer engage in new JV formation. The first term of the third line accounts for direct diffusion that a Foreign leader may catch up with the Home leader's productivity level by learning through the JV. The second term in the same line represents the change in value due to the exogenous termination of the JV.

**Optimal innovation and joint venture costs.** From the value function and the first order conditions, the optimal innovation rate of firm $i$ can be expressed as

$$x_{hjt} = x_{ht}(\mathbf{m};\mathcal{J}) = \left(\frac{V_{ht}(\mathbf{m} + (1,1,0);\mathcal{J}) - V_{ht}(\mathbf{m};\mathcal{J})}{\alpha_{Hr} w_{Ht}}\right)^{\frac{1}{\gamma-1}}, \qquad \mathcal{J} \in \{0,1\}. \tag{4.8}$$

The optimal joint venture rate is expressed as follows:

$$d_{hjt} = d_{ht}(\mathbf{m}) = \left(\frac{V_{ht}(\mathbf{m};1) - V_{ht}(\mathbf{m};0) - C_t(\mathbf{m})}{\alpha_{Hd} w_{Ht}}\right)^{\frac{1}{\gamma-1}}. \tag{4.9}$$

The innovation and JV rates are functions of technology gaps $\mathbf{m}$.

**Joint venture fee.** With a successful JV formation probability $d_{hjt}$, a Home leader pays (or receives) a fee to (or from) a Foreign leader, determined through Nash bargaining:

$$\begin{aligned} C_t(\mathbf{m}) = \operatorname*{argmax}_{C} & \left\{ \left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C\right)^{\xi} \times \left(\Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) + C\right)^{1-\xi} \right\} \\ \text{s.t.} \qquad & \Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C \geq 0, \qquad \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) + C \geq 0 \\ = (1-\xi) & \Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - \xi \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) \end{aligned} \tag{4.10}$$

where $\xi$ is the bargaining power of Home leaders and $\Delta^{\mathrm{JV}}$ denotes for changes in the value functions after forming a JV: $\Delta^{\mathrm{JV}} V_{it}(\mathbf{m}) = V_{it}(\mathbf{m};1) - V_{it}(\mathbf{m};0)$, $i \in \{h, \tilde{h}, f, \tilde{f}\}$.

When Foreign leaders are more lagged behind (i.e., $m^F > 0$), Home leaders are more likely to receive adoption fees from Foreign leaders, as Foreign leaders gain significantly from direct diffusion and, therefore, are willing to pay more for forming JVs (i.e., $C_t(\mathbf{m}) \geq 0$). Conversely, when $m^F \leq 0$, Foreign leaders do not gain from direct diffusion, but Home leaders still benefit from additional JV profits. In this case, Home leaders pay adoption fees to Foreign leaders (i.e., $C_t(\mathbf{m}) < 0$).

When Home leaders form JVs, they anticipate future profit declines due to productivity improvements among Foreign firms due to both direct and indirect knowledge diffusion from JVs. They internalize these dynamic profit losses and are compensated through bargaining fees from Foreign leaders. However, they do not internalize the profit losses incurred by Home fringe firms due to JV formation, resulting in a negative competition externality. Similarly, Foreign leaders do not internalize knowledge diffusion to Foreign fringe firms, leading to underinvestment in JVs.

Combining Equation (4.10) and (4.9), the optimal JV rate is as follows:

$$d_{hjt} = d_{ht}(\mathbf{m}) = \left( \frac{\xi(\Delta^{\mathrm{JV}} V_{Ht} + \Delta^{\mathrm{JV}} V_{Ft})}{\alpha_{Hd} w_{Ht}} \right)^{\frac{1}{\gamma-1}}.$$

The optimal JV rate increases with the total surplus $(\Delta^{\mathrm{JV}} V_{Ht} + \Delta^{\mathrm{JV}} V_{Ft})$, given the bargaining power parameter $\xi$. The total surplus from JV increases with the technology gap, because additional JV profits and Chinese rivals' productivity gains from diffusion increase with technology gaps.

**Market clearing.** Asset markets clear in each period: $A_{Ht} = \int_0^1 \sum_{i \in \mathcal{I}_H} V_{ijt} \mathrm{d}j$, where the right-hand side is the sum of the values of all firms in Home. Goods markets clear according to

$$\sum_{i \in \mathcal{I}_H} p_{ijt} y_{ijt} + \sum_{i \in \mathcal{I}_{Fjt}} p^*_{ijt} y^*_{ijt} = P_{Ht} C_{Ht}, \qquad \forall j \in [0,1].$$

Labor markets clear as

$$L_H = \int_0^1 \left( \sum_{i \in \mathcal{I}_H} l_{ijt} + \alpha_{Hr} \frac{(x_{ijt})^\gamma}{\gamma} + \alpha_{Hd} \frac{(d_{ijt})^\gamma}{\gamma} \right) \mathrm{d}j,$$

where the right-hand side is the sum of labor demand by Home firms. The similar market clearing conditions hold in Foreign, and trade is balanced.

**Equilibrium.** The distribution over states $\mu_t(\mathbf{m}; \mathcal{J})$ evolve endogenously according to firms' optimal innovation and JV decisions. Its law of the motion is given by equation (C.8). We formally define a Markov perfect equilibrium and balanced growth path.

**Definition 1.** *A Markov perfect equilibrium is a set of prices $\{r_{ct}, w_{ct}, p_{ijt}, p^*_{ijt}, P^T_{jt}, P^N_{jt}, P_{jt}\}$ and goods and factor allocations $\{l_{ijt}, x_{ijt}, d_{ijt}, y_{ijt}, y^*_{ijt}, C^{NT}_{ct}, C^T_{ct}\}$ such that (i) representative households maximizes utility; (ii) firms maximize profits; (iii) goods, labor, and asset markets clear for each country and time; and (iv) the transition of $\mu_t(\mathbf{m}; \mathcal{J})$ evolves according to firms' optimal $x_{ijt}$ and $d_{ijt}$.*

**Definition 2.** *A balanced growth path is the equilibrium defined in Definition 1 in which* $\{w_{ct}, C_{ct}, A_{ct}\}$ *grow at a constant rate* $g$*, and* $r_{ct}$ *and* $\mu_t(\mathbf{m}; \mathcal{J})$ *are constant over time.*

### 4.6 Taking Stock: Negative Competition Externality

The novel feature of our model is the negative externality associated with JVs on fringe firms. Direct and indirect knowledge diffusion from JVs to Foreign firms enhance their global competitiveness, reducing Home firms' profits. Home leaders may over-invest in JVs as they do not internalize profit losses incurred by domestic fringe firms, while they internalize their own future losses through bargaining fees. Knowledge diffusion intensities ($\phi$ and $\delta^D$) and leaders' demand shifters $\psi$ govern magnitude of this externality. Higher diffusion intensities intensify future competitive pressures on Home fringe firms. Higher demand shifters make leaders hold larger market shares and align their JV decisions more closely with total industry profits, reducing the negative externality on fringe firms.

Beyond this, our model features other common market failures of step-by-step innovation frameworks. Innovation generates knowledge diffusion to domestic firms, leading to a classic positive externality. Oligopolistic market power causes firms to produce below socially optimal levels.

## 5. Taking the Model to the Data

Home and Foreign refer to the US and China. Each product of the tradable sector conceptually maps to a manufacturing SIC 4-digit industry. We solve the transition of the model starting from the initial condition in the year 1997 (two years before the start of our sample period), until it converges to the balanced growth path. Calibrating along the transition is important in out setup, because China experienced rapid growth during our sample period. The initial technology gaps between US and Chinese leaders are randomly drawn from a normal distribution $N(\mathcal{D}, \mathcal{V})$, parametrized by the mean $\mathcal{D}$ and variance $\mathcal{V}$. A positive $\mathcal{D}$ means that, on average, US leaders start with higher productivity than Chinese leaders.

We introduce time-varying import tariffs of both countries, $t_t^{US}$ and $t_t^{CN}$, to capture the post-WTO shifts in US-China trade policy. These tariffs apply uniformly across all products, and agents have perfect foresight over their future paths. JVs exporting to the US face the corresponding US import tariff.

With these additional elements, we calibrate total 24 parameters in 3 steps. First, we take 10 parameters directly from the data, externally calibrate 4 parameters from the literature, and jointly estimate 10 parameters using the simulated method of moments (SMM). Given an initial guess for the jointly estimated parameters, we solve for the model's transition. Along this transition path, we compute the model moments and calculate their distance from the data counterparts, and estimate the parameters that minimize this distance.

We take the 10 parameters $\{L_H, L_F, \beta, \chi, \kappa, \xi, g^{NT}, v, t_t^H, t_t^F\}$ directly from the data. The Home labor

Table 5: Estimation Results

| Parameter | Value | Description | Source / Main target |
|---|---|---|---|
| *Directly from data* | | | |
| $L_F/L_H$ | 2.83 | Labor supply of China relative to US | Human-capital adj. pop. (Lee and Lee, 2016) |
| $\beta$ | 0.40 | Tradable consumption share | 1997 US Benchmark IO table |
| $\chi$ | 0.08 | JV exit rate | Avg. exit rate in CN (Chen et al., 2023) |
| $\mathcal{V}$ | 0.7 | Variance of initial technology gap | Variance of productivity ratio in 1999 |
| $\kappa, \xi$ | 0.54 | US JV profit share | Avg. equity share of MNE |
| $g^{NT}$ | 0.017 | Productivity growth rate in non-tradable sector | Avg. growth rate of GDP per capita in US, 2011–2019 |
| $t_t^H, t_t^F$ | | US/CN import tariff rates | Avg. import tariff rates |
| *Externally calibrated* | | | |
| $\rho$ | 0.03 | Time preference | Literature |
| $\sigma$ | 4 | Elast. of subst. | Broda and Weinstein (2006) |
| $\gamma$ | 2 | Innovation/JV cost curvature | Acemoglu et al. (2018) |
| $\tau^x$ | 2.85 | Iceberg trade cost | Bai et al. (2024) |
| *Internally calibrated by SMM* | | | |
| $\alpha_{Hr}$ | 0.65 | US R&D cost scale parameter | Avg. R&D / sales of US firms |
| $\alpha_{Fr}$ | 0.76 | CN R&D cost scale parameter | Long-run avg. gap= 0 |
| $\alpha_{Hd}$ | 1.17 | US JV scale parameter | Avg. JV sales shares |
| $\lambda$ | 1.12 | Step size | GDP growth rate in the US |
| $\mathcal{D}$ | 20.0 | Avg. technology gap | 1999 mfg. value-added / emp. US/CN ratio |
| $\delta^F$ | 0.024 | Prob. of exo. knowl. diffusion within country | 2020 mfg. value added / emp. US/CN ratio |
| $\psi$ | 0.25 | Leader & JV demand shifter | Mfg. US Compustat firm sales / gross output |
| $\phi$ | 0.15 | Prob. of direct knowl. diffusion | Direct effect on Chinese parents, Fig. 1 |
| $\tau^z$ | 1.84 | JV iceberg technology cost | Sectoral regression results in US, Table 4 |
| $\delta^D$ | 0.027 | Prob. of exo. knowl. diffusion within country | Sectoral regression results in China, Table 1 |

***Notes.*** This table reports calibrated values of the parameters and the summary of the calibration strategy.

is normalized to $L_H = 1$, while Foreign labor is set to $L_F = 2.83$, based on the human capital-adjusted population in China relative to the US (Lee and Lee, 2016). The consumption share of tradable-sectors $\beta$ is set to 0.4 based on the 1997 US Benchmark input-output table. The exit rate of JVs $\chi$ is set to 0.08, based on the average exit rate of Chinese firms reported by Chen et al. (2023).

The JV profit share $\kappa$ is set to 0.54 based on the average equity share of MNEs in JV firms calculated from Orbis, based on the JV Law. The bargaining power of US leaders in JV fees is also set to $\xi = 0.54$. $g^{NT}$ is set to be the average growth rate of US real GDP per capita (2011 to 2019). $\mathcal{V}$ is set to 0.7, which is the variance of US-China labor productivity ratio across manufacturing sectors in 1999. We directly take $t_t^H$ and $t_t^F$ from the data as the import-weighted average tariffs in manufacturing sectors.

The 4 parameters $\{\rho, \sigma, \gamma, \tau^x\}$ are externally calibrated from the literature. We set the discount factor $\rho = 0.03$ as standard in the literature. We set $\gamma = 2$ to match the elasticity of innovation with respect to R&D following Acemoglu et al. (2018). The iceberg trade cost between the US and China is set to $\tau^x = 2.85$ following Bai et al. (2024).

The remaining 10 parameters $\boldsymbol{\Theta} = \{\alpha_{Hr}, \alpha_{Fr}, \alpha_{Hd}, \lambda, \mathcal{D}, \phi, \tau^z, \psi, \delta^F, \delta^D\}$ are jointly estimated by minimizing the distance between the model moments $M_m(\mathbf{\Theta})$ and their data counterparts $M_m^D$:

$$\min_{\mathbf{\Theta}} \sum_{m=1}^{10} \left( \frac{M_m^D - M_m(\mathbf{\Theta})}{\frac{1}{2}(M_m^D + M_m(\mathbf{\Theta}))} \right)^2 .$$

We choose moments that are relevant and informative about the 10 parameters.

The US R&D cost scale parameter $\alpha_{Hr}$ is calibrated to match the average R&D-to-sales ratio of R&D for manufacturing firms in Compustat (1999-2013). China's $\alpha_{Fr}$ is calibrated to match both countries to have the same average productivity level in the balanced growth path.[42] The JV cost scale parameter $\alpha_{Hd}$ is estimated to match the sales share of JVs in China. This moment is informative because with higher costs, there will be less JV investments and therefore the sales shares will be smaller. Because the step size parameter $\lambda$ governs long-run growth rate, we calibrate $\lambda$ to match the US long-run GDP growth rate (2011-2019).

The initial technology gap $\mathcal{D}$ is calibrated to match the initial 1999 value-added-per-employee ratio between China and the US. We calibrate the cross-country diffusion parameter $\delta^F$ to match the 2020 long-run value-added-per-employee ratio; higher $\delta^F$ implies faster convergence of China. The leaders' demand shifter $\psi$ is calibrated to match the overall share of US Compustat manufacturing firm sales to total US gross manufacturing output (Brault and Khan, 2024).

We pin down the direct diffusion parameter $\phi$, the exogenous within-country diffusion parameter $\delta^D$, and the JV iceberg technology cost $\tau^z$ using the facts 1, 2, and 3, respectively. The detailed procedure is outlined in Appendix D.1. We calibrate $\phi$ to match the average of the post-event study coefficients from the pooled diff-in-diff specification by running the analogous regression using model-generated data.[43] Because $\delta^D$ governs within-country diffusion, it directly relates to the fact 2. Because $\tau^z$ is associated with JVs' productivity losses, higher values imply weaker competition for US fringe firms, relating to the fact 3. To calibrate these two parameters, we run regression analogously to equation (3.3) using fringe firms in the US and China and fit the OLS estimates in column 1 of Tables 1 and 3, respectively.[44]

Table 5 summarizes the estimation results. The model moments closely match their data counterparts (Panel A of Table 6). We obtain a value of $\mathcal{D} = 20.0$, implying that the productivity of US firms is roughly 9 times larger initially than Chinese firms on average. $\phi$ is estimated to be 0.15 while $\delta^F = 0.024$. This implies that having JV increases the diffusion intensity from 2.4% to 17.4%. $\tau^z = 1.84$ suggests that JV productivity is 46% lower than their US leaders.

The model also captures two non-targeted moments. First, it predicts a positive relationship between the initial US-China technology gap and sectoral JV exposure: larger gaps boost JV incentives

[42] By targeting this ratio, we obtain $\alpha_{Fr} > \alpha_{Hr}$, because China has a larger labor endowment. When $\alpha_{Hr} = \alpha_{Fr}$ holds, China has higher average productivity levels than the US in the balanced growth path.

[43] Specifically, we run $y_{imt} = \beta\big(1[\text{Post}_{mt}] \times \mathbb{1}[\text{JV Partner}_{it}]\big) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}$, where the estimated $\beta$ gives the average of the post-event coefficients in equation (3.1). We obtain the estimate of 0.20, statistically significant at the 1% level.

[44] The sample restriction to fringe firms in the model is consistent with the FDI exposure in equation (3.4) which excludes own JV subsidiaries.

Table 6: Targeted and Non-Targeted Moments in the Model and the Data

| Moment | Model | Data |
|---|---|---|
| *Panel A. Targeted Moments* | | |
| US indirect effects of JV on sales (col 1, Panel A, Table 4) | −0.200 | −0.177 |
| CN indirect effects of JV on sales (col 1, Panel A, Table 1) | 0.098 | 0.122 |
| Direct effect on CN partners (Panel A, Figure 1) | 0.208 | 0.200 |
| Avg. US GDP per capita growth, 2011–2019 | 0.017 | 0.017 |
| Avg. R&D-to-sales ratio, Compustat mfg. firms | 0.073 | 0.073 |
| JV sales shares in CN | 0.118 | 0.110 |
| Mfg. value added per emp. ratio (CN / US), 1999 | 0.084 | 0.084 |
| Mfg. value added per emp. ratio (CN / US), 2020 | 0.397 | 0.382 |
| Leader firms' sales share | 0.279 | 0.280 |
| Long-run avg. productivity ratio | 0.999 | 1.000 |
| *Panel B. Non-Targeted Moments* | | |
| Sectoral regression, JV exposure & initial gap | 0.161 | 0.169 |
| US indirect effects of JV on R&D (col. 11, Panel A, Table 4) | −0.187 | −0.203 |

***Notes.*** This table reports targeted and non-targeted moments in both the model and the data. Appendix D.1 details how the model's objects map to the estimated firm- and sector-level regression coefficients of the data.

because they generate greater total surplus from JV—both through higher JV profits and larger productivity gains from diffusion. This relationship is also confirmed by the data. Second, it reproduces the observed negative effect of JV exposure on US firms' R&D spending (col. 11, Panel A of Table 4).

# 6. Quantitative Exercises

## 6.1 Did US Multinationals Transfer Too Much Technology?

Using the calibrated model, we first examine whether the US transferred too much technology to China through JVs in terms of US welfare. We consider a counterfactual scenario in which the US government restricts JV investment since 1999, and compare its welfare to the baseline scenario with JVs. In this counterfactual, firms are no longer allowed to establish new JVs, while existing JVs remain in place until they exit exogenously. We assume that this policy change is an unanticipated shock to all the agents.

Table 7 reports the welfare effects in consumption-equivalent variation.[45] The JV restriction improves US welfare by 1.3% but reduces China's welfare by 10.3%.[46] In the counterfactual, the US-China technology gap widens and China's speed of convergence slows down (Panels A and B of Figure 2) be-

[45] We solve for $\Psi$ that satisfies $\int_{t=0}^{T} \exp(-\rho t) \log(C_{Ht}) dt = \int_{t=0}^{T} \exp(-\rho t) \log\Big(\hat{C}_{Ht}(1+\Psi)\Big) dt$ for a sufficiently large $T$.

[46] These welfare numbers are comparable to welfare losses when moving to autarky (i.e., shutting down all trade and JVs by letting $\tau^x, \alpha_{Hd} \to \infty$), which amount to −8.70% for the US and −24.03% for China. They exceed the losses predicted by static trade models because autarky also depresses innovation rates and long run growth.

Table 7: Baseline vs. Counterfactual Scenarios: Welfare Effects (%)

| Counterfactual | Restricting JV investments | | | |
|---|---|---|---|---|
| | in 1999 | in 1999 coordinated JV | in 1999 technology gap ≥ 5 | in 2025 |
| | (1) | (2) | (3) | (4) |
| US | 1.28 | −0.64 | 1.35 | −0.51 |
| China | −10.26 | −1.82 | −10.37 | −2.32 |

***Notes.*** This table reports consumption-equivalent welfare changes for the US and China under four counterfactuals: restricting JVs in 1999 (column 1), restricting JVs in 1999 with coordinated JV decisions in both the baseline and counterfactual (column 2), restricting JVs in 1999 only for technology gaps larger than 5 (i.e., $m^F \geq 5$), and restricting JVs in 2025 (measured in 2025; column 4).

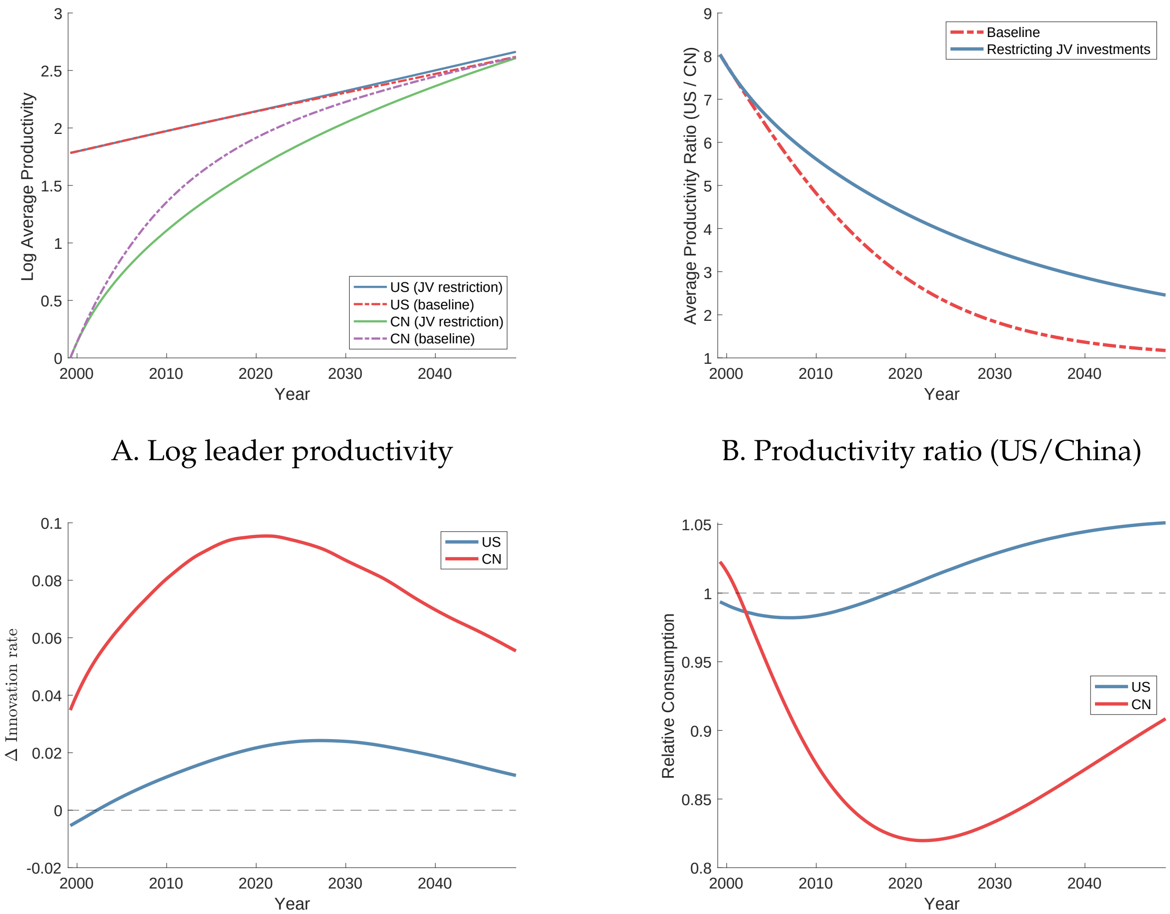
cause Chinese leaders' productivity growth slows down due to reduced knowledge diffusion through JVs, while US leaders' productivity rises slightly due to higher innovation rates (Panel C). In the absence of JVs, Chinese firms substitute toward innovation for JVs as a way to improve their productivity, increasing R&D but not enough to make up for lost knowledge diffusion from JVs.

Although the net welfare change is positive for the US and negative for China, Panel D reveals richer dynamics in relative consumption. In the short run, US consumption falls immediately after the JV restriction as US leaders lose JV fee revenues and profits. Over time, however, US firms' relatively higher productivity and higher innovation boost their global competitiveness, and US consumption surpasses the baseline around 20 years later. China experiences the opposite: its consumption share initially declines alongside slower productivity growth, then gradually recovers after 20 years as the technology gap narrows and diffusion plays a smaller role once the economies approach their balanced growth paths.

There are mainly two opposing forces driving the higher US innovation rate under the counterfactual. First, the option-value effect: firms have greater incentive to innovate when they can form a JV. By innovating before JV formation, US leaders raise total surplus from JV and capture part of it through negotiated fees. This explains why the average innovation rate drops immediately after the 1999 restriction (Panel A of Figure 3). Second, there is a composition effect. In the baseline, products with JVs exhibit lower innovation intensities than those without conditional on technology gaps (Panel B) because, even though JVs enlarge market size and raise marginal returns to R&D (Bustos, 2011), they also accelerate spillovers to Chinese rivals, eroding future profits and thus dampening the returns to innovation through heightened competition (Aghion et al., 2001). Moreover, any extra surplus from innovation that benefits Chinese partners cannot be recouped once the JV fee is paid. The two peaks in Panel B arises due to escape competition effects.[47] In our calibration, the competition effect dominates

[47] The two peaks at $m^F \approx -5$ and $m^F \approx 13$ reflect "defensive" and "expansionary" innovation motives (Akcigit et al., 2023). When $m^F \approx -5$, US and Chinese leaders are neck-and-neck (after accounting for wage differentials and trade costs) in the US, so even a small productivity gain sharply raises domestic profits and prompts US leaders to invest more in R&D to defend domestic market share. When firms are neck-and-neck, market share and profits are much more sensitive to productivity

Figure 2: Baseline vs. Restricting Joint Venture Investments in 1999: Dynamics of Productivity, Innovation, and Consumption




A. Log leader productivity

B. Productivity ratio (US/China)

C. Innovation rate difference

D. Relative consumption

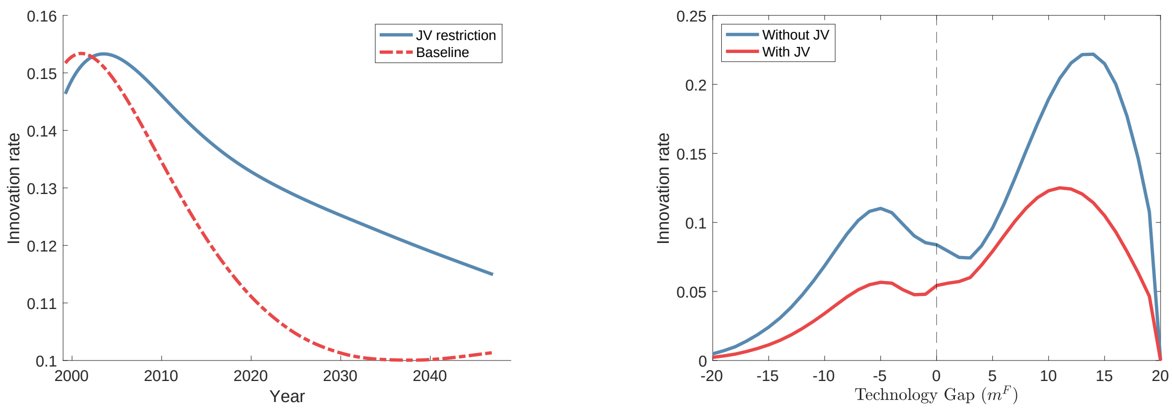
***Notes.*** This figure compares dynamics under the counterfactual (JV restriction in 1999) to the baseline. Panel A shows log average leader productivity for the US and China; Panel B shows the US–China productivity ratio; Panel C plots the difference in their average innovation rates (counterfactual minus baseline); and Panel D plots relative consumption.

the market size benefits; as JVs are established in more products, the overall mix shifts toward those with lower innovation rates.[48] Consequently, over the medium term, the competition-driven composition effect dominates the option-value effect, leading to higher average innovation rates under the

gains. The asymmetry between the peaks ($-5$ vs. 13) reflects China's lower wages due to larger labor endowment. When $m^F \approx 13$, US leaders are neck-and-neck in China, so they increase R&D to expand abroad. China also similarly shows two peaks (Appendix Figure D2). One important difference from Akcigit et al. (2023) is that JV-driven diffusion tends to close the productivity gap, moving it toward zero, where innovation rates fall below the two peaks.

[48] In Appendix Figure D3, we consider two alternative parametrizations. First, by setting $\kappa = 1$, we make the US takes the whole JV profits, which amplifies market size effects. Then, the gap of innovation rates between the baseline and counterfactual narrows. Second, we shut down direct diffusion by setting $\phi = 0$, eliminating the competition effect. In this case, the sign of the innovation-rate difference flips. Innovation rates under the baseline exceed those in the counterfactual scenario.

Figure 3: US Innovation Rate over Time and Technology Gap




A. US average innovation rate

B. US innovation rate over $m^F$ (baseline)

***Notes.*** Panel A plots the average innovation rate in baseline and counterfactual scenarios. Panel B plots the innovation rate in the baseline scenario in 2025 over technology gaps between US and Chinese leader firms $m^F$. $m^F > 0$ denotes the case where US leaders higher productivity than Chinese leaders. In Panel B, technology gaps between domestic firms are set to $m^{DF} = m^{DH} = \bar{m}$.

Table 8: Baseline vs. Restricting Joint Venture Investments in 1999: Net Present Value of Real Profits and Labor Income

| | Baseline | Restricting JV | Changes (%) |
|---|---|---|---|
| US leader profit (own + JV + JV fee) | 0.048 | 0.035 | −27.44 |
| Own profit | 0.033 | 0.035 | −6.06 |
| JV profit | 0.009 | 0.000 | n/a |
| JV fee revenue | 0.007 | 0.000 | n/a |
| US fringe profit | 0.065 | 0.068 | 5.13 |
| US labor income | 0.887 | 0.910 | 2.58 |
| US total real income | 1.000 | 1.013 | 1.29 |
| CN leader profit (own + JV + JV fee) | 0.041 | 0.036 | −10.82 |
| Own profit | 0.041 | 0.036 | −12.20 |
| JV profit | 0.006 | 0.000 | n/a |
| JV fee payment | −0.006 | 0.000 | n/a |
| CN fringe profit | 0.062 | 0.058 | −6.88 |
| CN labor income | 0.897 | 0.802 | −10.59 |
| CN total real income | 1.000 | 0.896 | −10.37 |

***Notes.*** This table reports the net present value of real profits and labor income, deflated by each country's price index and normalized by baseline total real income, under the counterfactual that JVs are banned in 1999 versus the baseline. Leader profits include own profits, JV profits, and JV fees.

JV restriction.

Next, we decompose the welfare effects of restricting JVs by income sources, as shown in Table

Table 9: Robustness. Baseline vs. Restricting Joint Venture in 1999. Alternative Assumptions

| | $\Delta$ US Welfare (%) | $\Delta$CN Welfare (%) | $\Delta$ US Innovation rate (%) | $\Delta$ CN Innovation rate (%) |
|---|---|---|---|---|
| Baseline | 1.28 | −10.26 | 1.61 | 7.70 |
| No innovation | 0.45 | −15.88 | 0 | 0 |
| Love of variety | 0.75 | −10.88 | 1.61 | 7.79 |
| Constant markup | 1.33 | −8.30 | 1.47 | 5.38 |

***Notes.*** This table reports the effects of restricting JV in 1999 with alternative parameterizations. $\Delta$ Welfare is expressed in consumption-equivalent units, and $\Delta$ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

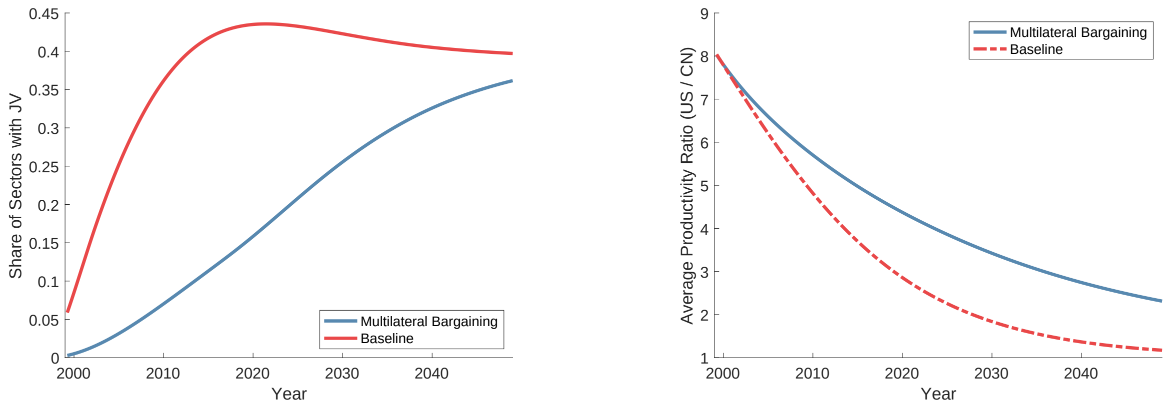
8. Here, real income is the sum of discounted leader profits (own profits + JV profits + JV fees), fringe profits, and labor income, all normalized by baseline total real income and deflated by each country's price index. Under the US counterfactual, leader profits fall because JV profits vanish and early JV fees received from Chinese partners are lost. Fringe profits rise first due to the removal of JV competition and later because reduced technology diffusion eases rivalry from Chinese firms. Labor income increases due to higher labor demand by domestic firms, and real income increases further from lower price levels driven by higher innovation. In contrast, in China both leader and fringe profits decrease because of reduced diffusion, and labor income declines due to lower labor demand. At the same time, slower diffusion pushes price levels higher. Appendix Figure D4 presents these income dynamics over time.

To further examine the mechanism behind the welfare results and robustness to modeling assumptions, we consider alternative modeling assumptions, reported in Table 9. When we shut down innovation channel, achieved by setting R&D cost parameter values to infinity, the JV restriction still increases welfare by 0.45%, although the magnitude decreases by 65% (0.45% vs. 1.28%). Without innovation, JVs are the only sources of productivity improvement in China except for exogenous diffusion, leading to larger welfare losses for China. This implies that innovation responses to JVs play an important role for the welfare effects. We also consider preserving love of variety instead of shutting down it. Because JV introduces additional variety, by restricting the JV, the welfare gains become lower due to this loss of love of variety, but it is still positive at 0.75%. Finally, we consider constant markups, as in a standard monopolistic competitive case. Overall, our results remain robust to alternative modeling assumption. Moreover, our results also remain robust to sensitivity checks for the key parameters ($\phi$, $\delta^F$, $\delta^D$, $\mathcal{D}$, and $\kappa$), reported in Appendix Table D1.

## 6.2 Can Coordinating Joint Venture Investments Improve Welfare?

We showed that there can be over-investment of JV as US leaders do not incorporate US fringe firm's profits and that this over-investment can lower US welfare. To correct it, we introduce coordinated JV decisions: a JV can only be established if US leaders compensate fringe firms for their expected losses. More specifically, we add an additional bargaining problem between US leaders and fringe

Figure 4: Coordinated Joint Venture Decisions. Baseline vs. Restricting Joint Venture Investments in 1999: Dynamics of Joint Venture Rates and Productivity




A. JV rate B. Productivity ratio (US/China)

***Notes.*** This figure reports the dynamics of the share of sectors with JVs (Panel A) and the productivity ratio between US and Chinese leaders (Panel B) under the 1999 JV restriction with coordinated decisions, in which US leaders compensate domestic fringe firms for JV-related profit losses through multilateral bargaining.

firms, besides the one between US and Chinese leaders. We solve these two bargaining problems jointly using the Nash-in-Nash concept (Horn and Wolinsky, 1988), assuming that US leaders hold full bargaining power in the leader-fringe negotiation.

The modified bargaining outcomes are:

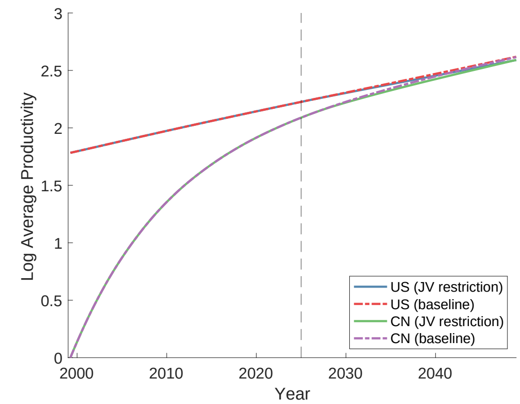
$$C = (1-\xi)\left\{\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})\right\} - \xi \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}), \qquad C^E = -\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}), \tag{6.1}$$

where $C^E$ is the fee paid by US leaders to fringe firms. They now internalize both own and fringe profits. This can be shown from the above expression that the sum of value changes $\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})$ enters the bargaining fee in equation (6.1), whereas in the baseline case, only $\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m})$ entered in equation (4.10). Because US leaders have full bargaining power, they compensate fringe firms exactly by their losses, as shown by $C^E = -\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})$.

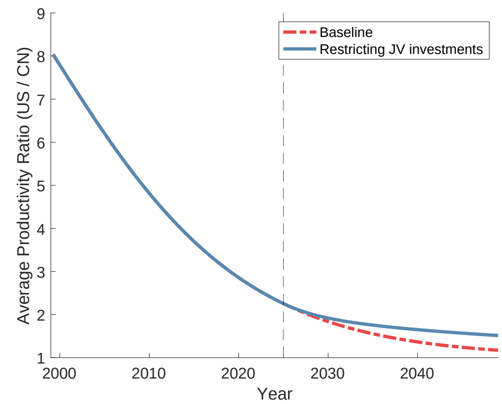
Coordinating JV decisions alters the welfare impacts of the 1999 restriction. Under coordination, restricting JV now decreases US welfare by 0.6% and Chinese welfare by 1.8%, compared to the case without JV restriction (col. 2 of Table 7).[49] By requiring US leaders to compensate their own fringe firms, coordination internalizes the negative externality and makes JVs more costly, which in turn makes JVs improve US welfare. As Panel A of Figure 4 shows, fewer sectors choose JVs under coordination. With fewer JVs, technology diffusion to China slows and China's convergence rate declines (Panel B). China's welfare loss is smaller because coordination leads to fewer JVs.

[49] Coordinated JV raises US welfare by 1.8% relative to the uncoordinated baseline, exceeding the welfare gain from restricting JV investments in the baseline case.

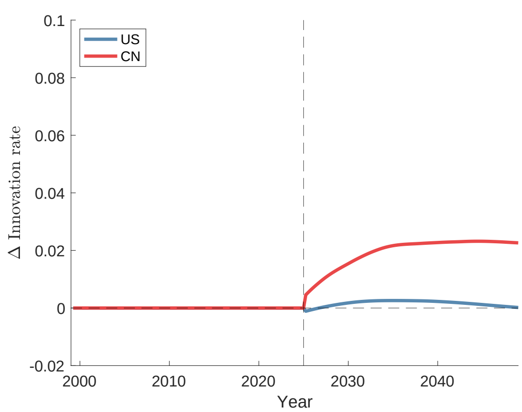
Figure 5: Baseline vs. Restricting Joint Venture Investments in 2025: Dynamics of Productivity, Innovation, and Consumption



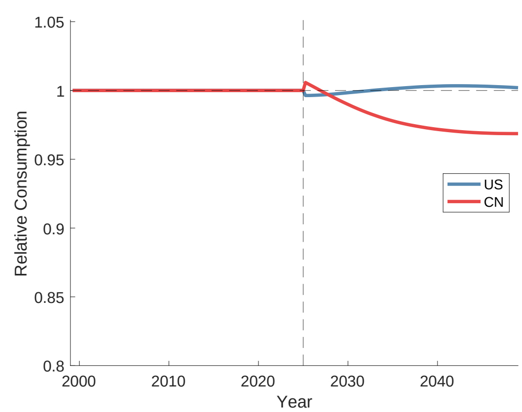

A. Log leader productivity




B. Productivity ratio (US/China)




C. Innovation rate difference




D. Relative consumption

***Notes.*** This figure compares dynamics under the counterfactual (JV restriction down in 2025) to the baseline. The dashed vertical line represents the year in which the JV restriction was imposed. Panel A shows log average leader productivity for the US and China; Panel B shows the US–China productivity ratio; Panel C plots the difference in their average innovation rates (counterfactual minus baseline); and Panel D plots relative consumption.

### 6.3 Restricting Joint Venture Investments in 1999 Conditional on Technology Gaps

Because JVs are more likely to be established in sectors with larger technology gaps (see the non-targeted moment in Table 6, they generate larger diffusion in sectors where the US initially holds a comparative advantage. This selection arises because total surplus from a JV is higher in these sectors, which are split between two leaders.[50] As a result, diffusion from JVs biases China's productivity growth toward sectors of US strength.

Well-known theoretical results (Dornbusch et al., 1977; Samuelson, 2004) show that the US can

[50] In a neoclassical trade model, Alviarez (2019) similarly shows that MNEs tend to enter sectors in which the host country has a comparative disadvantage. Although our mechanisms differ, both frameworks yield the same selection pattern.

lose welfare when China becomes similar in terms of relative productivity with the US.[51] To explore this, we simulate a state dependent restriction that bans JVs whenever $m^F \geq 5$ (i.e., when US leaders are at least 5 steps ahead). We select the threshold of 5 because it generated the largest welfare gains.[52] The policy can be viewed as an effort to maintain US comparative advantage in high-tech sectors. Under this policy, US welfare rises by 1.35% relative to the baseline, which means that it is preferable to the total ban of JVs, which raised welfare by 1.28% (col. 3 of Table 7). However, by eliminating the option to form JVs when $m^F \geq 5$, this policy has an unintended consequence: it reduces the value of maintaining $m^F \geq 5$ for US firms and thus dampens their incentives to innovate.

### 6.4 What if the US Restricts Joint Venture Investments in 2025?

Next, we consider restricting JV investments in 2025 rather than 1999, reflecting more recent policy debates. In contrast to the 1999 case, it lowers US welfare (col. 4 of Table 7; measured in 2025) by 0.51%, flipping the sign. By then, the US-China technology gap becomes much smaller (Panel A of Figure 5), so diffusion—and the resulting negative externality—are weaker. Although the restriction still slightly widens the gap, the losses from foregone JV profits and market access outweigh the modest gains from reduced diffusion. Overall, the welfare gains of banning JVs decline over time as the technology gap narrows (Appendix Figure D6), so the effect depends critically on the technology gap at the moment of restriction.

## 7. Conclusion

Amid the economic and geopolitical rivalry between the US and China, there are ongoing debates on whether US firms transferred to much technology to China and whether policies curbing such transfers should be more broadly implemented. In our oligopolistic competition model with knowledge spillovers, we have shown that leading US firms may over-invest in joint ventures in China, as they do not consider the negative competition effect through spillovers on other US firms, providing a justification for policy interventions.

Our benchmark policy experiment assumed no response from the Chinese government. Developing a model in which the two countries' governments strategically interact through various policies will be an important next step, especially given China's active industrial policy, including the quid-pro-quo policy.

Furthermore, since tariffs will affect the negative competition effects from knowledge spillovers to Chinese firms, one compelling avenue for future research is to explore how optimal tariffs and joint venture policies will interact—a direction we have taken in other ongoing work.

On the empirics side, our novel results on the direct and indirect effects of joint ventures on Chinese and US firms could be further refined to better understand the role of firm heterogeneity. For instance,

[51] See di Giovanni et al. (2014) and Liu et al. (2024) for quantitative analyses of such biased productivity growth.

[52] Appendix Figure D5 reports welfare effects over different gaps.

how do the characteristics of different US leader firms (e.g., size, R&D intensity) influence their joint venture decisions and the extent of technology leakage? Similarly, how do the absorptive capacities of different Chinese firms affect their ability to benefit from spillovers? In addition, future research could explore alternative measures and methodologies to better quantify the direct and indirect effects of technology transfer through joint ventures.

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# ONLINE APPENDIX

# A. Appendix: Data

## A.1 Data Construction

**Annual Survey of Industrial Enterprises.** We drop observations with missing or negative values for sales, capital (fixed assets), or employment, and retain only manufacturing firms with CIC 4-digit codes between 1300 and 4400. The Annual Survey of Industrial Enterprises covers all state-owned and private firms with annual sales above 5 million RMB before 2010 and 20 million RMB thereafter. To ensure consistency, we apply the 20 million RMB threshold throughout the sample period. Industry codes follow CIC 1994 from 1998 to 2001 and CIC 2002 from 2002 to 2013. We harmonize industry classifications using concordance tables from the Industrial Classification for National Economic Activities and the CIC 1994–2002 concordance provided by Brandt et al. (2012).

**Compustat.** We drop observations with missing or negative values for sales, capital (PPEGT), or employment. We restrict our sample to manufacturing firms, SIC 4-digit codes between 2000 and 3999. We also obtain each firm's total foreign sales (including both exports and sales from foreign affiliates) from the historical geographic segment data. For Global Compustat—used only in the robustness check in Appendix Table B7—we apply the same cleaning procedure as for US Compustat.

**Mapping between the Chinese balance sheet and customs datasets.** We clean firm name, postal code, and phone number variables of the Annual Survey of Industrial Enterprises and the customs datasets. Then, we match the two datasets based on these variables following standard practices (e.g. Chor et al., 2021).

**Mapping between the Chinese balance sheet and the Orbis Global datasets.** The matching proceeds in two steps. First, we use the Legal Entity Identifier, a standard unique identifier, to link across datasets. For firms without a Legal Entity Identifier, we apply fuzzy matching based on firm names in Chinese characters using Orbis's built-in bulk matching algorithm. To ensure reliability, we retain only "A-level" matches, which represent the highest match quality according to Orbis's classification. Lower-confidence matches (B or C levels) are excluded to reduce matching errors.

**Mapping between the Chinese balance sheet and CNIPA patent data sets.** We clean firm names in both datasets by removing non-distinctive terms (e.g., "Co., Ltd." or "Limited Liability Company"). In the patent data, where multiple applicants are listed in a single field separated by colons, we extract and standardize each applicant name. Then, we match the two datasets based on cleaned names.

**Mapping between US Compustat and the Orbis Global datasets.** To merge the Compustat and Orbis databases, we again use Orbis's built-in bulk matching algorithm, which relies on fuzzy matching. We apply the same criterion—A-level confidence—as in the mapping between the Chinese balance sheet and the Orbis dataset.

**Mapping between the US Compustat and USPTO.** We use Kogan et al. (2017) data in which the assignees of the patents in USPTO are matched with Compustat firm identifier (gvkey).

**Mapping between the Orbis Global datasets and USPTO.** When the Orbis firm identifier is matched with Compustat firm identifier, we use Kogan et al. (2017) data to map into USPTO assignee IDs. The remaining firms are merged using fuzzy matching algorithm. We first clean the firm names as in the previous step, and then apply fuzzy matching. To ensure correct matching, we only keep the pairs with similarity score higher than 0.9.

## A.2 Descriptive Statistics

Table A1: Descriptive Statistics of US Compustat Firms

| Variable | Sale ($1M) (1) | Emp (1K) (2) | Capital ($1M) (3) | $\mathbb{1}$[Export > 0] (4) | Export ($1M) (5) |
|---|---|---|---|---|---|
| | *Panel A. All firms* | | | | |
| Mean | 1884.16 | 5.1 | 1042.65 | 0.63 | 2124.40 |
| Median | 137.2 | 0.53 | 49.52 | 1 | 22.5 |
| Standard deviation | 10739.49 | 17.65 | 7931.23 | 0.48 | 16301.53 |
| N (unique firms) | 4,355 | 4,355 | 4,355 | 4,355 | 4,355 |
| N | 31,301 | 31,301 | 31,301 | 31,301 | 31,301 |
| | *Panel B. MNEs that have ever formed a JV in China* | | | | |
| Mean | 17512.27 | 38.92 | 11255.25 | 0.97 | 25868.10 |
| Median | 4727.98 | 18.55 | 2661.24 | 1 | 5044.55 |
| Standard deviation | 43212.95 | 50.85 | 35469.32 | 0.16 | 75428.38 |
| N (unique firms) | 74 | 74 | 74 | 74 | 74 |
| N | 948 | 948 | 948 | 948 | 948 |
| | *Panel C. MNEs that have ever formed a JV or WOFE in China* | | | | |
| Mean | 9477.95 | 23.39 | 5613.49 | 0.97 | 13425.87 |
| Median | 2434.12 | 10.08 | 1181.77 | 1 | 2866.96 |
| Standard deviation | 29006.98 | 36.99 | 23021.56 | 0.16 | 49741.26 |
| N (unique firms) | 180 | 180 | 180 | 180 | 180 |
| N | 2,374 | 2,374 | 2,374 | 2,374 | 2,374 |

**Notes:** This table reports descriptive statistics for US firms from Compustat. Panel A includes all firms; Panel B includes multinational firms that have ever formed joint ventures in China; and Panel C includes multinational firms that have ever established either joint ventures (JVs) or wholly-owned foreign enterprises (WOFEs). All monetary values are in 2007 USD.

Table A2: Descriptive Statistics of Chinese Firms

| Variable | Sale ($1M)<br>(1) | Emp (1K)<br>(2) | Capital ($1M)<br>(3) | $\mathbb{1}$[Export > 0]<br>(4) | Export ($1M)<br>(5) | $\mathbb{1}$[State-owned firm]<br>(6) |
|---|---|---|---|---|---|---|
| | *Panel A. All firms* | | | | | |
| Mean | 27.93 | 0.38 | 7.50 | 0.28 | 4.62 | 0.04 |
| Median | 7.87 | 0.20 | 1.34 | 0 | 0 | 0 |
| SD | 481.07 | 1.18 | 69.07 | 0.45 | 80.19 | 0.19 |
| N (unique firms) | 548,294 | 548,294 | 548,294 | 548,294 | 548,294 | 548,294 |
| N | 2,260,771 | 2,260,771 | 2,260,771 | 2,260,771 | 2,260,771 | 2,260,771 |
| | *Panel B. Chinese partners that ever formed JVs with foreign MNEs* | | | | | |
| Mean | 252 | 2.06 | 86.07 | 0.63 | 38.37 | 0.1 |
| Median | 24.48 | 0.51 | 7.19 | 1 | 1.78 | 0 |
| SD | 1314.61 | 7.90 | 508.50 | 0.48 | 414.62 | 0.31 |
| N (unique firms) | 2,261 | 2,261 | 2,261 | 2,261 | 2,261 | 2,261 |
| N | 18,835 | 18,835 | 18,835 | 18,835 | 18,835 | 18,835 |
| | *Panel C. JV subsidiaries* | | | | | |
| Mean | 45.68 | 0.41 | 12.03 | 0.56 | 11.04 | |
| Median | 9.80 | 0.23 | 2.07 | 1 | 0.51 | |
| SD | 271.49 | 0.79 | 74.38 | 0.5 | 101.54 | n/a |
| N (unique firms) | 29,755 | 29,755 | 29,755 | 29,755 | 29,755 | |
| N | 126,379 | 126,379 | 126,379 | 126,379 | 126,379 | |
| | *Panel D. JV and WOFE subsidiaries* | | | | | |
| Mean | 43.04 | 0.44 | 10.84 | 0.63 | 16.05 | |
| Median | 9.95 | 0.23 | 2.20 | 1 | 1.88 | |
| SD | 240.63 | 0.99 | 59.28 | 0.48 | 144.95 | n/a |
| N (unique firms) | 59,294 | 59,294 | 59,294 | 59,294 | 59,294 | |
| N | 266,360 | 266,360 | 266,360 | 266,360 | 266,360 | |

**Notes:** This table reports descriptive statistics for Chinese firms from the Annual Survey of Industrial Enterprises. Panel A includes all firms; Panel B includes partner firms that have ever formed joint ventures with foreign multinational firms; Panel C includes joint ventures; and Panel D includes joint ventures or wholly-owned enterprises. All monetary values are in 2007 USD.

# B. Appendix: Empirics

## B.1 Concordance

First, we construct the concordance between 4-digit CIC and 1987 SIC codes in two steps. We first map CIC 2002 to NAICS 1997 using the concordance table by Ma et al. (2014), and then apply the 1997 NAICS-1987 SIC concordance table from the US Census. This process results in a mapping where each unique 4-digit CIC code corresponds to multiple 4-digit SIC 1987 codes. For those CIC codes with multiple mappings, to give more weights on industries with larger size, we assign weights based on 1995 gross output from the US NBER-CES manufacturing database.

Second, using the constructed mapping above, we construct the FDI exposure at the 1987 SIC 4-digit level. Specifically, the denominator of the FDI exposure in equation (3.4) is computed as

$$\text{Total sales}^{\text{CN}}_{j,98} = \sum_{h \in \text{CIC}(j)} \omega^j_h \sum_{g \in \mathcal{F}_{h,98}} \text{Sale}_{gh,98},$$

where $\mathcal{F}_{h,98}$ is a set of firms with CIC code $h$ in 1998, CIC($j$) is a set of CIC 4-digit codes that has a mapping with SIC $j$, and $\omega^j_h$ is a weight of CIC $h$ assigned for SIC $j$. The numerator $\Delta\text{FDI sales}_j$ is computed similarly for FDI affiliates:

$$\Delta\text{FDI sales}_j = \sum_{h \in \text{CIC}(j)} \omega^j_h \sum_{g \in \mathcal{J}_{h,12}} \text{Sale}_{gh,12} - \sum_{h \in \text{CIC}(j)} \omega^j_h \sum_{g \in \mathcal{J}_{h,99}} \text{Sale}_{gh,99},$$

where $\mathcal{J}_{ht}$ is a set of FDI affiliates with CIC $h$ code in year $t$. For the regression models in Tables (3) and (4), we use the FDI exposure defined at the 4-digit SIC level.

Finally, for the FDI exposure used for the regression model in Table 1, we weight the SIC 4-digit level FDI exposure using the mapping and the weights constructed in the first step:

$$\Delta\text{FDI}_h = \sum_{j \in \text{SIC}(h)} \omega^h_j \Delta\text{FDI sales}_j,$$

where $\omega^h_j$ is a weight of SIC $j$ assigned for CIC $h$ that are mapped to multiple 4-digit SIC codes.

## B.2 Additional Evidence on Indirect Knowledge Diffusion

In this subsection, we present additional evidence on indirect knowledge diffusion using citation flows, a commonly used proxy for knowledge flows in the literature. We show that foreign MNEs that formed JVs began receiving more citations from non-partner Chinese firms, compared to control MNEs that did not form any JVs.

The treatment group consists of MNEs that formed JVs. To construct the control group, we follow a two-step matching procedure. First, among MNEs that did not form any JVs, we select those from the same country and technological field as the treated firms. In the second step, we identify MNEs that are similar to the treated firms based on the inverse hyperbolic sine transformation of cumulative citations, cumulative patents, annual citations received, and annual new patents produced, using Mahalanobis distance. The matching procedure results in 132 pairs of treated and control MNEs, with 132 unique firms in both the treated and control groups.

Using the constructed pairs, we run the following fully-stacked event-study specification:

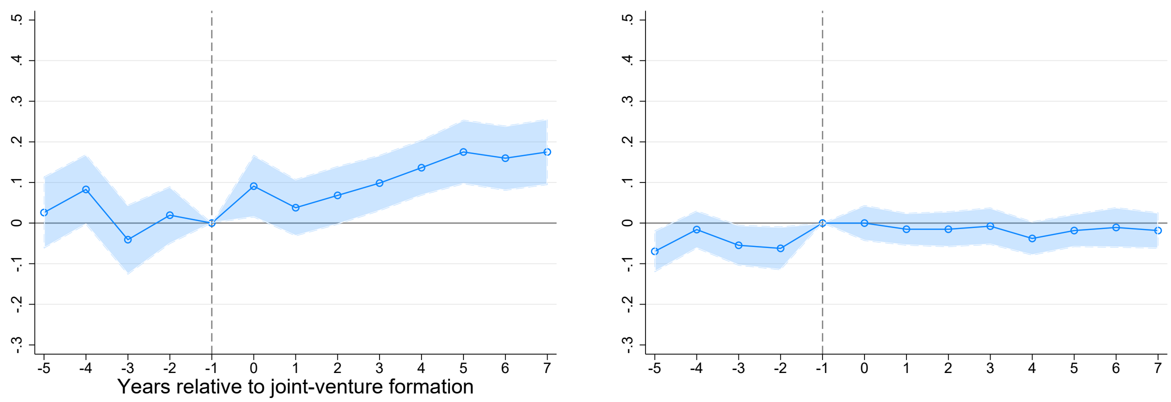
$$y_{imt} = \sum_{\tau=-5}^{5} \beta_\tau \left( D_{mt}^{\tau} \times \mathbb{1}[\text{JV Formation}_{imt}] \right) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}, \tag{B.1}$$

where $\mathbb{1}[\text{JV Formation}_{imt}]$ is a dummy of treatment, and $D_{mt}^{\tau}$ are event study variables. $\delta_{im}$ and $\delta_{mt}$ are firm-pair and pair-year fixed effects. Standard errors are clustered at the pair level.

The dependent variables are dummies of receiving positive citations by non-partner Chinese firms. If there were knowledge diffusion, we expect non-partner firms to increase citations because their technologies may build upon knowledge transferred from MNEs.

Figure B1 reports the estimated coefficients. We observe that citation received by non-partner Chinese firms began to increase only after JV formation, and there are no signs of pretrends. However, a potential concern is that the increase in citations may not be due to indirect knowledge diffusion, but rather because the MNEs involved in the JV experienced innovation or productivity shocks, which made their patents more attractive for citation. To address this concern, we also examine citations from non-Chinese firms, using them as the dependent variable in Panel B. If the increase in citations were driven by innovation or productivity shocks, we would expect to see a similar increase in citations from non-Chinese firms at the same time. However, we find no such evidence, ruling out this alternative explanation.

Figure B1: After Forming Joint Ventures, Foreign Multinationals Received More Citations from Chinese Firms




A. Dummy of receiving citations by Chinese firms excluding own JV

B.Dummy of receiving citations by non-Chinese firms (Placebo)

**Notes:** This figure illustrates the event study estimation results of equation (B.1). 95% confidence intervals, based on standard errors clustered at the pair levels, are reported. $\beta_{-1}$ is normalized to zero. In Panels A and B, the dependent variables are dummies of receiving citations by non-partner Chinese firms, and by non-Chinese firms, respectively. All specifications include firm-pair and pair-year fixed effects.

## B.3 Additional Figures and Tables

Table B1: Balance of Matched Sample. Direct Effects of Joint Venture Formation on Chinese Partner Firms

| | JV | | | | Non-JV | | | | (Col. 1 - Col. 5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean (1) | Median (2) | SD (3) | N (4) | Mean (5) | Median (6) | SD (7) | N (8) | $t$-stat (9) | $p$-val (10) |
| Log sale | 17.42 | 17.28 | 1.67 | 629 | 17.46 | 17.29 | 1.63 | 2,506 | 0.36 | 0.55 |
| Log emp. | 6.39 | 6.27 | 1.42 | 629 | 6.42 | 6.37 | 1.50 | 2,506 | 0.15 | 0.70 |
| Log sales per emp. | 11.03 | 10.92 | 1.14 | 629 | 11.04 | 10.93 | 1.25 | 2,506 | 0.01 | 0.90 |
| Log capital | 16.28 | 16.17 | 1.85 | 629 | 16.2 4 | 16.16 | 1.90 | 2,506 | 0.26 | 0.61 |
| Log capital per emp. | 9.90 | 9.85 | 1.22 | 629 | 9.82 | 9.79 | 1.34 | 2,506 | 0.97 | 0.33 |
| Ihs export | 9.62 | 14.33 | 8.21 | 629 | 9.86 | 14.16 | 8.22 | 2,506 | 0.17 | 0.68 |
| Dum export | 0.57 | 1 | 0.50 | 629 | 0.58 | 1 | 0.49 | 2,506 | 0.12 | 0.73 |
| Ihs cumulative patent | 0.64 | 0 | 1.36 | 629 | 0.66 | 0 | 1.34 | 2,506 | 0.02 | 0.90 |
| Dum. patent stock | 0.26 | 0 | 0.44 | 629 | 0.28 | 0 | 0.45 | 2,506 | 0.28 | 0.60 |
| Ihs yearly new patent | 0.42 | 0 | 1.12 | 629 | 0.42 | 0 | 1.11 | 2,506 | 0.01 | 0.94 |
| Dum. yearly new patent | 0.16 | 0 | 0.37 | 629 | 0.17 | 0 | 0.37 | 2,506 | 0.09 | 0.77 |

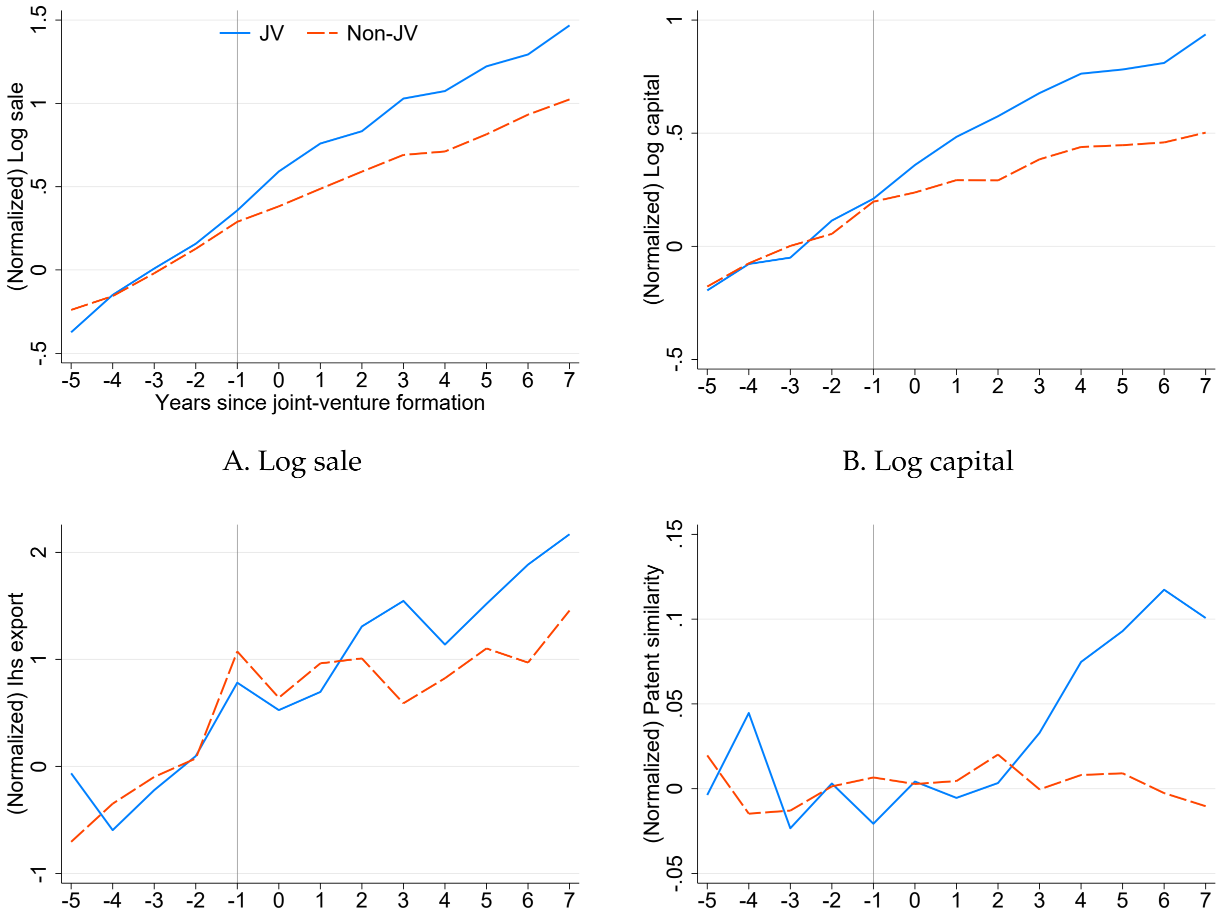
***Notes.*** This table presents descriptive statistics for treated and control firms from five to one years before the event. Column 9 reports t-statistics for the mean differences between winners and losers, while Column 10 provides the corresponding p-values (in brackets), computed using standard errors clustered at the firm and match levels. All monetary values are expressed in 2007 US dollars.

Table B2: Balance Test. Direct Effects of Joint Venture Formation on Chinese Partner Firms

| Dep. var. | Dummies of JV status | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| Log sale | −0.003 | | | | | | | | | | |
| | (0.005) | | | | | | | | | | |
| Log emp | | −0.003 | | | | | | | | | |
| | | (0.007) | | | | | | | | | |
| Log sales per emp | | | −0.001 | | | | | | | | |
| | | | (0.009) | | | | | | | | |
| Log capital | | | | 0.002 | | | | | | | |
| | | | | (0.004) | | | | | | | |
| Log capital per emp | | | | | 0.008 | | | | | | |
| | | | | | (0.008) | | | | | | |
| Ihs export | | | | | | −0.001 | | | | | |
| | | | | | | (0.001) | | | | | |
| Dum export | | | | | | | −0.008 | | | | |
| | | | | | | | (0.022) | | | | |
| Ihs cumulative patent stock | | | | | | | | −0.001 | | | |
| | | | | | | | | (0.009) | | | |
| Dum cumulative patent stock | | | | | | | | | −0.015 | | |
| | | | | | | | | | (0.029) | | |
| Ihs yearly patent | | | | | | | | | | −0.001 | |
| | | | | | | | | | | (0.010) | |
| Dum yearly patent | | | | | | | | | | | −0.009 |
| | | | | | | | | | | | (0.029) |
| Mean dep. var. | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| # clusters (match) | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 |
| # clusters (pair) | 868 | 868 | 868 | 868 | 868 | 868 | 868 | 868 | 868 | 868 | 868 |
| N | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 | 3,135 |

***Notes.*** Standard errors in parentheses are clustered at the match and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table presents the covariate balance test for the event study sample, covering five to one years before the event. The dependent variable is a dummy indicating treatment status. The regressors include log sales, log employment, log sales per employment, log fixed assets, log fixed assets per employment, the inverse hyperbolic sine transformation of exports, export dummies, cumulative patent stock, and yearly new patents.

Figure B2: Raw Plots. Direct Effects of Joint Venture Formation on Chinese Partner Firms




A. Log sale

B. Log capital

C. Ihs export

D. Technological proximity

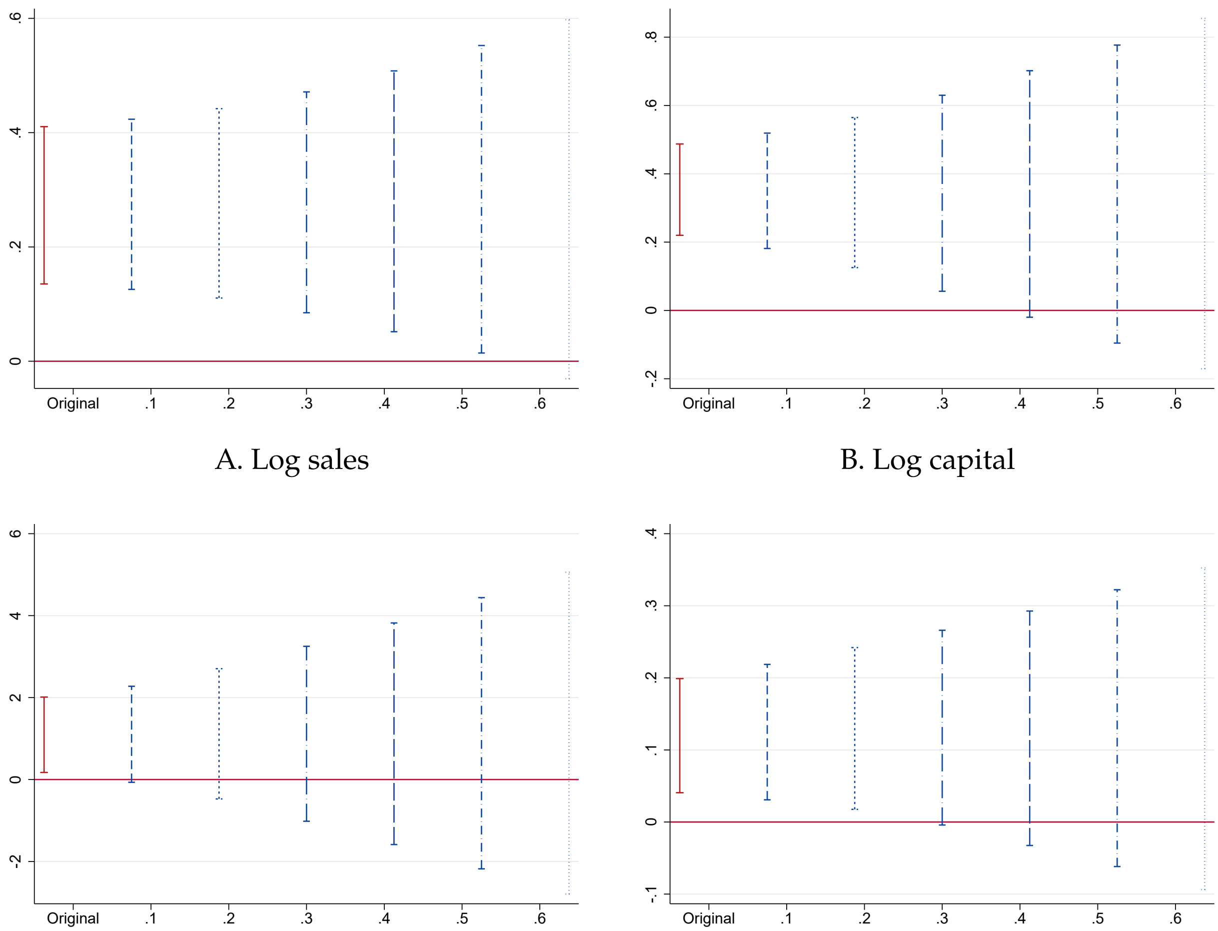
***Notes.*** The figure presents the mean trends of log sales, log capital, the inverse hyperbolic sine transformation of exports, and technological proximity (measured by patents) for treated and control groups. The treated group is represented by the blue solid line, while the control group is shown with the red dashed line. All values are normalized by their pre-event averages.

Table B3: Direct Effects of Joint Venture Formation on Chinese Partner Firms

| | Baseline outcomes | | | | Alternative outcomes | | | |
|---|---|---|---|---|---|---|---|---|
| Dep. var. | Log sale | Log capital | Ihs export | Technological proximity | Log emp. | Dum. export | Ihs patent stock | Ihts annual patent |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 5 years before | −0.03 | 0.02 | 0.78 | 0.03 | −0.01 | 0.07 | −0.12 | −0.13 |
| | (0.10) | (0.11) | (0.77) | (0.06) | (0.12) | (0.05) | (0.16) | (0.17) |
| 4 years before | −0.02 | −0.04 | 0.07 | 0.06 | 0.04 | 0.00 | 0.01 | 0.12 |
| | (0.08) | (0.09) | (0.61) | (0.04) | (0.09) | (0.04) | (0.12) | (0.12) |
| 3 years before | 0.03 | −0.05 | 0.36 | 0.03 | 0.02 | 0.02 | 0.01 | 0.06 |
| | (0.05) | (0.09) | (0.56) | (0.03) | (0.08) | (0.04) | (0.10) | (0.11) |
| 2 years before | −0.01 | 0.06 | 0.23 | 0.04 | −0.00 | 0.01 | −0.02 | 0.01 |
| | (0.04) | (0.06) | (0.44) | (0.03) | (0.05) | (0.03) | (0.06) | (0.08) |
| 1 year before | | | | | | | | |
| Year of the event | 0.13*** | 0.11** | 0.14 | 0.02 | 0.04 | −0.00 | 0.04 | 0.12 |
| | (0.04) | (0.05) | (0.35) | (0.03) | (0.04) | (0.03) | (0.04) | (0.08) |
| 1 year after | 0.16*** | 0.16*** | 0.20 | 0.02 | 0.14** | 0.01 | 0.14* | 0.17* |
| | (0.05) | (0.05) | (0.48) | (0.03) | (0.06) | (0.03) | (0.08) | (0.10) |
| 2 years after | 0.13* | 0.25*** | 0.62 | 0.05 | 0.12 | 0.04 | 0.25** | 0.25** |
| | (0.07) | (0.07) | (0.58) | (0.04) | (0.09) | (0.04) | (0.11) | (0.12) |
| 3 years after | 0.22*** | 0.31*** | 1.09* | 0.12** | 0.07 | 0.05 | 0.30** | 0.35*** |
| | (0.08) | (0.08) | (0.56) | (0.05) | (0.11) | (0.04) | (0.12) | (0.12) |
| 4 years after | 0.27*** | 0.35*** | 1.01* | 0.14*** | 0.14* | 0.06 | 0.44*** | 0.47*** |
| | (0.08) | (0.08) | (0.57) | (0.05) | (0.09) | (0.04) | (0.14) | (0.14) |
| 5 years after | 0.32*** | 0.37*** | 1.29* | 0.14*** | 0.05 | 0.08* | 0.43*** | 0.37*** |
| | (0.10) | (0.09) | (0.68) | (0.05) | (0.13) | (0.05) | (0.15) | (0.14) |
| 6 years after | 0.38*** | 0.43*** | 1.24 | 0.15*** | 0.07 | 0.06 | 0.55*** | 0.62*** |
| | (0.11) | (0.10) | (0.83) | (0.05) | (0.15) | (0.05) | (0.16) | (0.17) |
| 7 years after | 0.46*** | 0.54*** | 1.12 | 0.15*** | 0.15 | 0.09* | 0.45** | 0.40** |
| | (0.11) | (0.12) | (0.85) | (0.06) | (0.15) | (0.05) | (0.19) | (0.19) |
| Fixed effects | Firm-match, Match-year | | | | | | | |
| Mean dep. var. | 17.77 | 16.44 | 10.39 | 0.22 | 6.48 | 0.58 | 0.95 | 0.62 |
| # Cluster (match) | 176 | 176 | 176 | 106 | 176 | 176 | 176 | 176 |
| # Cluster (firm) | 859 | 859 | 859 | 321 | 859 | 859 | 859 | 859 |
| N | 7,457 | 7,457 | 7,457 | 1,746 | 7,457 | 7,457 | 7,457 | 7,457 |

***Notes.*** Standard errors, shown in parentheses, are clustered at the match and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimated event study coefficients of equation (3.1). $\beta_{-1}$ is normalized to zero. In columns 1-8, the dependent variables are log sales, log capital, inverse hyperbolic sine transformation of exports, technological proximity (equation (3.2)), log employment, dummies of exports, and inverse hyberbolic sine transformation of cumulative patent stock and yearly new patents, respectively. All specifications include match-firm and match-year fixed effects. In Column 4, the sample size decreases due to firms with zero patent stock, as technological proximity is only well-defined for firms with positive patent stock in both the treated and control groups.

Figure B3: Robustness. Sensitivity to Violations of the Parallel Trend Assumption. Direct Effects of Joint Venture Formation on Chinese Partner Firms




A. Log sales

B. Log capital

C. Ihs export

D. Tech. proximity

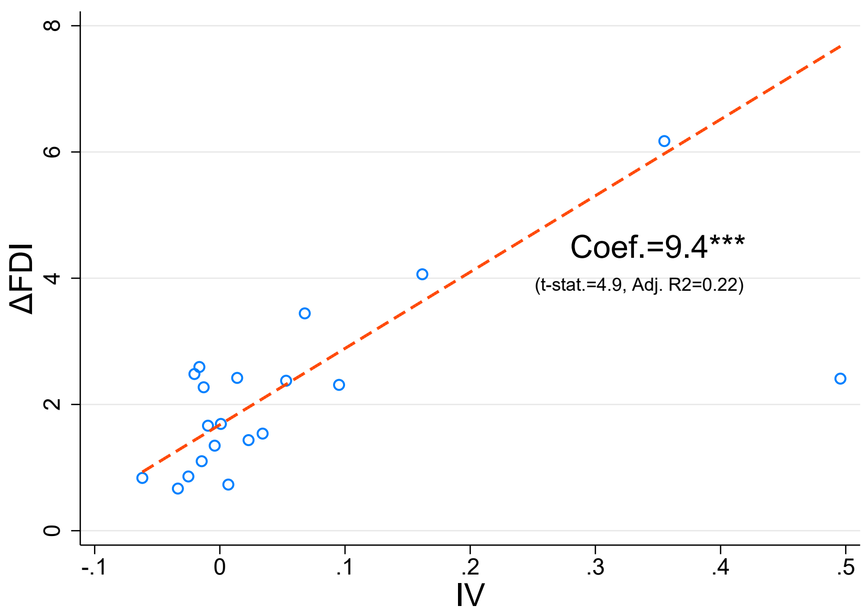
***Notes.*** This figure presents results of the sensitivity checks for potential violations of the parallel trend assumption based on Rambachan and Roth (2023). The figure reports the estimated 90% confidence intervals, based on standard errors two-way clustered at the firm and match levels, for $\beta_4$ of equation (3.1) over different values of $M$ which is a parameter that governs magnitude of violations to the parallel trend assumption: $\Delta^{RM}(M) = \{\delta : \forall t \geq 0, |\delta_{t+1} - \delta_t| \leq M \times \max_{s \leq 0} |\delta_{s+1} - \delta_s|$, where $\max_{s \leq 0} |\delta_{s+1} - \delta_s|$ is the maximum pre-treatment violation of parallel trends. $M = 1$ is a natural benchmark, which bounds the worst-case post-treatment difference in trends by the maximum in pre-treatment periods (Rambachan and Roth, 2023, p.2563). $\beta_{-1}$ is normalized to zero. In Panels A, B, C, and D, the dependent variables are log sales, log capital, inverse hyperbolic sine transformation of exports, and technological proximity (equation (3.2)), respectively.

Table B4: Robustness. Alternative Number of Matches and Depreciation Rates for Patent Stock. Direct Effects of Joint Venture Formation on Chinese Partner Firms

| Robustness | Alt. number of matches | | | | | | Alt. dep. rate | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2 | 3 | 5 | 2 | 3 | 5 | 0 | 0.2 | 0.5 |
| Dep. var. | Log sales | | | Technological proximity | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| 5 years before | −0.16 | −0.17 | −0.09 | 0.05 | −0.04 | −0.02 | 0.03 | 0.03 | 0.02 |
| | (0.13) | (0.11) | (0.10) | (0.06) | (0.08) | (0.09) | (0.05) | (0.06) | (0.06) |
| 4 years before | −0.10 | −0.13 | −0.09 | 0.06 | 0.02 | 0.04 | 0.03 | 0.05 | 0.06 |
| | (0.09) | (0.08) | (0.08) | (0.04) | (0.03) | (0.04) | (0.03) | (0.04) | (0.04) |
| 3 years before | −0.03 | −0.02 | −0.00 | 0.07* | 0.04 | 0.04 | 0.03 | 0.03 | 0.02 |
| | (0.07) | (0.06) | (0.05) | (0.04) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| 2 years before | −0.01 | −0.02 | −0.02 | 0.06 | 0.02 | 0.04 | 0.03 | 0.03 | 0.04 |
| | (0.05) | (0.04) | (0.04) | (0.04) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| 1 years before | | | | | | | | | |
| Event year | 0.11** | 0.13*** | 0.11*** | 0.04 | 0.02 | 0.02 | 0.03 | 0.02 | 0.01 |
| | (0.04) | (0.04) | (0.03) | (0.04) | (0.04) | (0.03) | (0.02) | (0.03) | (0.03) |
| 1 year after | 0.14** | 0.16*** | 0.16*** | 0.03 | 0.03 | 0.00 | 0.03 | 0.02 | 0.02 |
| | (0.06) | (0.05) | (0.05) | (0.04) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| 2 year after | 0.09 | 0.12* | 0.13* | 0.05 | 0.04 | 0.01 | 0.04 | 0.04 | 0.05 |
| | (0.07) | (0.07) | (0.07) | (0.05) | (0.04) | (0.04) | (0.03) | (0.04) | (0.04) |
| 3 year after | 0.15* | 0.22** | 0.22*** | 0.12** | 0.11** | 0.09** | 0.08** | 0.11** | 0.13*** |
| | (0.09) | (0.08) | (0.08) | (0.06) | (0.05) | (0.04) | (0.04) | (0.05) | (0.05) |
| 4 year after | 0.16* | 0.21** | 0.20** | 0.12* | 0.11** | 0.09** | 0.10** | 0.13*** | 0.14*** |
| | (0.09) | (0.09) | (0.08) | (0.06) | (0.05) | (0.04) | (0.04) | (0.05) | (0.05) |
| 5 year after | 0.27** | 0.30*** | 0.27*** | 0.13** | 0.12** | 0.09** | 0.11*** | 0.14*** | 0.14*** |
| | (0.11) | (0.11) | (0.09) | (0.06) | (0.06) | (0.04) | (0.04) | (0.05) | (0.05) |
| 6 year after | 0.28** | 0.25** | 0.23** | 0.11 | 0.11* | 0.08* | 0.11*** | 0.14*** | 0.16*** |
| | (0.13) | (0.12) | (0.10) | (0.07) | (0.06) | (0.04) | (0.04) | (0.05) | (0.05) |
| 7 year after | 0.35** | 0.32** | 0.31*** | 0.14* | 0.13** | 0.10** | 0.11** | 0.15** | 0.13** |
| | (0.14) | (0.13) | (0.11) | (0.07) | (0.06) | (0.05) | (0.05) | (0.06) | (0.05) |
| FE | Firm-match, Match-year | | | | | | | | |
| Mean dep. var. | 17.82 | 17.74 | 17.70 | 0.22 | 0.21 | 0.19 | 0.24 | 0.23 | 0.21 |
| # clusters (match) | 176 | 176 | 176 | 70 | 89 | 111 | 106 | 106 | 106 |
| # clusters (firm) | 523 | 692 | 1,030 | 176 | 253 | 412 | 321 | 321 | 321 |
| N | 4,462 | 6,046 | 9,055 | 971 | 1,462 | 2,500 | 1,746 | 1,746 | 1,746 |

***Notes.*** Standard errors, shown in parentheses, are clustered at the match and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimated event study coefficients of equation (3.1). $\beta_{-1}$ is normalized to zero. In columns 1-3 and 4-9, the dependent variables are log sales and technological proximity (equation (3.2)), respectively. In columns 1-6 and 7-9, we consider alternative numbers of matches and depreciation rates used for computing patent stock, respectively. All specifications include match-firm and match-year fixed effects. In Columns 4-9, the sample size decreases due to firms with zero patent stock, as technological proximity is only well-defined for firms with positive patent stock in both the treated and control groups.

Figure B4: First-Stage Relationship between the FDI Exposure and the IV




**Notes:** This figure illustrates the binscatter plot of the first-stage relationship between the IV (x-axis) and the FDI exposure (y-axis) at the SIC 4-digit level, with 20 equal-sized bins, controlling for the NTR gap and weighted by initial gross output. The red-line represents the estimated linear-fit, with an estimated coefficient of 9.4, which is statistically significant at the 1% level.

Table B5: Pre-trend and Shock Balance Test of the IV

| Balance variable | Coef. | SE | $p$-val. |
|---|---|---|---|
| *Panel A. Pre-trend* | | | |
| $\Delta$ Log gross output, 1993-1998 | 0.11 | (0.06) | [0.06] |
| $\Delta$ Log emp., 1993-1998 | 0.10 | (0.06) | [0.10] |
| $\Delta$ Log PPI, 1993-1998 | 0.05 | (0.05) | [0.35] |
| $\Delta$ US import (ex. CN, IN, JP, SK) / absorption, 1996-1998 | 0.04 | (0.02) | [0.12] |
| $\Delta$ US-CN import / absorption, 1996-1998 | −0.05 | (0.06) | [0.41] |
| *Panel B. Industry-level balance* | | | |
| US-CN import / absorption 1996 | −0.06 | (0.04) | [0.14] |
| US-IN import / absorption 1996 | −0.01 | (0.01) | [0.28] |
| CN-IN import / absorption 1996 | −0.02 | (0.01) | [0.15] |
| IN-CN import / absorption 1996 | −0.02 | (0.02) | [0.24] |
| JV sales share 1998 | 0.04 | (0.04) | [0.28] |
| Number of JV firms to total number of firms ratio 1998 | 0.02 | (0.01) | [0.12] |
| US import (ex. CN, IN, JP, SK) / absorption 1996 | 0.14 | (0.04) | [0.00] |
| Ratio of capital to wage-bills 1993 | 0.01 | (0.07) | [0.91] |
| Ratio of wage bills to value-added 1993 | 0.03 | (0.05) | [0.56] |
| R&D intensity 1993 | 0.00 | (0.01) | [0.81] |
| Production workers' share of employment 1993 | 0.27 | (0.06) | [0.00] |
| High-tech investment shares 1990 | −0.13 | (0.09) | [0.15] |
| Computer investment shares 1990 | −0.18 | (0.05) | [0.00] |
| N | | 383 | |

**Notes:** Standard errors clustered at the SIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS estimates obtained after regression industry-level characteristics on the IV. Each observation is a 4-digit SIC industry. All variables are standardized. R&D intensity is the 1993 sectoral mean of firms' R&D-to-sales ratios, calculated from Compustat. High-tech and computer investment shares are obtained from Acemoglu et al. (2016), varying at the SIC 3-digit levels. All regressions are weighted by the initial sector gross output.

Table B6: Firm-level Pre-trend. Correlations between the IV and Pre-1999 Firm Size Growth

| | US firms DHS growth, 1993-1998 | | | |
|---|---|---|---|---|
| Dep. var. | $\Delta$Sale<br>(1) | $\Delta$Emp.<br>(2) | $\Delta$Capital<br>(3) | $\Delta$Export<br>(4) |
| $\text{IV}_j$ | −2.78 | −3.77 | 17.83 | −15.05 |
| | (17.83) | (21.53) | (13.10) | (35.21) |
| Mean dep. var. | 13.43 | −1.23 | 16.27 | 67.39 |
| # Clusters | 102 | 102 | 102 | 94 |
| N | 723 | 723 | 723 | 565 |

**Notes:** Standard errors, clustered at the SIC-3 digit levels, are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the US firm-level pretrend result. The IV is defined in equation (3.5). In columns 1-4, the dependent variables are the DHS growth of sales, employment, capital, and exports between 1993 and 1998. All specifications include the NTR gap control. All regression models are weighted by initial sales.

Table B7: Robustness. Indirect Negative Competition Effects to Global Firms

| Dep. var. | ΔSale<br>(1) | ΔEmp<br>(2) | ΔCapital<br>(3) | ΔR&D<br>(4) |
|---|---|---|---|---|
| | *Panel B. OLS* | | | |
| $\Delta\text{FDI}_j$ | $-6.65^{**}$ | 0.38 | $-5.60^{**}$ | $-9.99^{***}$ |
| | (2.87) | (1.43) | (2.16) | (3.59) |
| $\text{NTRgap}_j$ | $-0.87$ | $-0.54$ | $-0.75$ | $-0.05$ |
| | (0.70) | (0.41) | (0.52) | (0.90) |
| | *Panel B. IV* | | | |
| $\Delta\text{FDI}_j$ | $-11.89^{***}$ | $-1.56$ | $-7.42^{*}$ | $-22.79^{***}$ |
| | (4.42) | (2.77) | (3.95) | (6.15) |
| $\text{NTRgap}_j$ | $-0.98$ | $-0.58$ | $-0.78$ | $-0.46$ |
| | (0.67) | (0.43) | (0.51) | (0.65) |
| KP-*F* | 44.65 | 44.65 | 44.65 | 14.77 |
| Mean dep. var. | 2.74 | $-2.84$ | $-14.87$ | 6.80 |
| # clusters | 106 | 106 | 106 | 72 |
| N | 642 | 642 | 642 | 253 |

**Notes:** Standard errors clustered at the SIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.3). Estimation samples include global firms, excluding those from China, India, South Korea, and US. The FDI exposure $\Delta\text{FDI}_{fj}$ and the IV are defined in equations (3.4) and (3.5), respectively. In columns 1-2, 3-4, and 5-6, the dependent variables are US firms' changes in log sales, log employment, and inverse hyperbolic sine transformation of export values, respectively, between 1999-2012. The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. The even columns include 1996 US import penetration (overall imports, excluding US, China, India, Japan, and South Korea, relative to domestic absorption), 1993 production worker shares, 1990 computer investment shares, and 1-digit industry dummies. KP-*F* is the Kleibergen-Papp F-Statistics. All regression models are weighted by initial sales.

Table B8: Robustness. Heterogeneous Effects based on R&D Intensity. Indirect Effects

| Sample | Chinese firms | | US firms | |
|---|---|---|---|---|
| Dep. var. | $\Delta$Sale | $\Delta$Emp | $\Delta$Sale | $\Delta$Emp |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}$[Low R&D inten.$_j$] $\times$ $\Delta\text{FDI}_{fj}$ | 11.98*** | 10.14*** | −15.52*** | −15.73*** |
| | (3.08) | (2.17) | (3.99) | (4.79) |
| $\mathbb{1}$[High R&D inten.$_j$] $\times$ $\Delta\text{FDI}_{fj}$ | 34.52* | 31.45* | −17.40*** | −17.95*** |
| | (17.61) | (17.41) | (3.45) | (4.04) |
| NTRgap$_j$ | 0.01 | 0.63** | −1.69* | −1.65 |
| | (0.33) | (0.29) | (0.90) | (1.07) |
| KP-$F$ | 3.59 | 3.59 | 5.04 | 5.04 |
| SW-$F$ (low R&D intensity) | 73.16 | 73.16 | 10.35 | 10.35 |
| SW-$F$ (high R&D intensity) | 12.21 | 12.21 | 97.93 | 97.93 |
| Mean dep. var. | 79.61 | −7.08 | 8.69 | −10.82 |
| # Clusters | 157 | 157 | 105 | 105 |
| N | 14,844 | 14,844 | 1,017 | 1,017 |

**Notes:** Standard errors clustered at the SIC-3 and CIC-3 digit levels are reported in parenthesis in columns 1-2 and 3-4, respectively. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.3). Estimation samples are Chinese and US firms in columns 1-2 and 3-4, respectively. $\mathbb{1}$[High R&D inten.$j$] is an indicator for sectors in the top quintile of the sectoral average of firm-level R&D-to-sales ratios in 1999, while $\mathbb{1}$[Low R&D inten.$j$] indicates the remaining sectors. The FDI exposure $\Delta\text{FDI}_{fj}$ and the IV are defined in equations (3.4) and (3.5), respectively. In columns 1 and 3, and 2 and 4, the dependent variables are sales and employment growth, respectively, between 1999-2012. The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. KP-$F$ is the Kleibergen-Papp F-Statistics. SW-$F$ is the Sanderson-Windmeijer F-Statistics. All regression models are weighted by initial sales.

Table B9: Additional Robustness Checks. Indirect Positive Spillovers to Chinese Firms

| Robustness | Alt. sample ex. FDI subsidiaries | Alt. FDI exposure domestic sales | Alt. IV only Japan | Alt. control China's FDI policy | Alt. clustering 4-digit level | Alt. sample period 1999-2007 | Alt. weight emp. |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | *Panel A. Dependent variable: ΔSale* | | | | | | |
| $\Delta\text{FDI}_{fj}$ | 11.45** | | 12.87*** | 13.52*** | 12.16*** | 19.20** | 13.30** |
| | (5.28) | | (3.51) | (4.75) | (3.03) | (7.51) | (5.27) |
| $\Delta\text{FDI}_{fj}$ (dom. sale) | | 12.86*** | | | | | |
| | | (3.76) | | | | | |
| Mean dep. var. | 81.74 | 79.61 | 79.61 | 79.61 | 79.61 | 44.12 | 84.04 |
| | *Panel B. Dependent variable: ΔEmp* | | | | | | |
| $\Delta\text{FDI}_{fj}$ | 8.56** | | 10.21*** | 9.73** | 10.31*** | 16.63*** | 10.74*** |
| | (3.41) | | (2.07) | (3.90) | (2.30) | (4.97) | (3.77) |
| $\Delta\text{FDI}_{fj}$ (dom. sale) | | 11.02*** | | | | | |
| | | (2.73) | | | | | |
| Mean dep. var. | −18.92 | −7.08 | −7.08 | −7.08 | −7.08 | −6.30 | −39.96 |
| NTR gap ctrl. | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KP-*F* | 36.73 | 20.15 | 69.83 | 34.83 | 49.97 | 80.37 | 21.01 |
| # clusters | 156 | 157 | 157 | 157 | 380 | 157 | 157 |
| N | 11978 | 14,844 | 14,844 | 14,844 | 14,844 | 18326 | 14834 |

**Notes:** Standard errors are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Standard errors are clustered at the CIC 3-digit in columns 1-4 and 6-7 and 4-digit levels in columns 5. This table reports the IV estimates of equation (3.3). $\Delta\text{FDI}_{fj}$ and the IV are defined in equations (3.4) and (3.5). In Panels A and B, the dependent variables are the DHS growth rates of sales and employment for Chinese firms, respectively. Columns 1 excludes all FDI subsidiaries (JV and WOFE). Column 2 uses domestic sales to measure FDI exposure, excluding exports. Columns 3 constructs the IV using only Japan's FDI in India. Column 4 includes additional controls including China's changes in the domestic FDI policy, log input tariffs, and log output tariffs between 2000 and 2007. Column 5 uses alternative clustering at the CIC 4-digit level. Column 6 uses an alternative sample period (1999-2007, pre-Great Recession). Column 7 considers an alternative weights using employment. All specifications include the NTR gap which is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. All specifications include dummies of state-owned firms and FDI affiliates, and province fixed effects. KP-*F* is the Kleibergen-Papp F-Statistics. Regression models are weighted by initial sales in columns 1-6 and by initial employment in column 7.

Table B10: Additional Robustness Checks. Sectors with Higher FDI Exposure Experienced Larger Chinese Export Growth and Greater Declines in US Manufacturing

| Robustness | Alt. FDI exposure domestic sales | Alt. IV only Japan | Alt. control China's FDI policy | Alt. clustering 4-digit level | Alt. sample period 1999-2007 | Alt. weight emp. |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *Panel A. Dependent variable: ΔUS-CN Import* | | | | | |
| $\Delta\text{FDI}_j$ | | 8.50*** | 8.53** | 8.30*** | 26.08*** | 7.95*** |
| | | (1.97) | (4.16) | (1.77) | (5.28) | (1.82) |
| $\Delta\text{FDI}_j$ (dom. sale) | 8.90*** | | | | | |
| | (2.23) | | | | | |
| Mean dep. | 136.68 | 136.68 | 136.68 | 136.68 | 125.66 | 134.94 |
| | *Panel B. Dependent variable: ΔOC-CN Import* | | | | | |
| $\Delta\text{FDI}_j$ | | 10.55*** | 9.57** | 10.39*** | 32.05*** | 10.41*** |
| | | (2.82) | (4.13) | (2.27) | (6.04) | (2.84) |
| $\Delta\text{FDI}_j$ (dom. sale) | 11.24*** | | | | | |
| | (3.15) | | | | | |
| Mean dep. var. | 146.98 | 146.98 | 146.98 | 146.98 | 128.96 | 145.78 |
| NTR gap ctrl. | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KP-*F* | 26.58 | 70.36 | 39.87 | 104.86 | 104.96 | 15.66 |
| N | 383 | 383 | 383 | 383 | 383 | 383 |

**Notes:** Standard errors are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Standard errors are clustered at the SIC 3-digit in columns 1-3 and 5-6 and 4-digit levels in column 4. This table reports the IV estimates of equation (3.6). The FDI exposure $\Delta\text{FDI}_j$ and the IV are defined in equations (3.4) and (3.5), respectively. In Panels A and B, the dependent variables are the DHS growth rates of US imports from China and the selected countries imports from China. Column 1 uses domestic sales to measure FDI exposure, excluding export components. Column 2 constructs the IV using only Japan's FDI in India. Column 3 includes additional controls including China's changes in the domestic FDI policy, log input tariffs, and log output tariffs between 2000 and 2007. Column 4 considers alternative clustering at the 4-digit industry level. Column 5 considers an alternative sample period (1999-2007, pre-Great Recession). Column 6 considers an alternative weight based on initial employment. All specifications include the NTR gap which is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. KP-*F* is the Kleibergen-Papp F-Statistics. Regression models are weighted by initial sales in columns 1-5 and by initial employment in column 6.

Table B11: Additional Robustness Checks. Indirect Negative Competition Effects to US Firms

| Robustness | Alt. sample ex. FDI MNEs | Alt. FDI exposure domestic sales | Alt. IV only Japan | Alt. control China's FDI policy | Alt. clustering 4-digit level | Alt. sample period 1999-2007 | Alt. weight emp. |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | *Panel A. Dependent variable: $\Delta$Sale* | | | | | | |
| $\Delta\text{FDI}_{fj}$ | $-15.33^{***}$ | | $-17.28^{***}$ | $-7.45^{*}$ | $-17.68^{***}$ | $-28.51^{***}$ | $-11.79^{***}$ |
| | (3.59) | | (3.64) | (4.39) | (3.74) | (6.48) | (2.90) |
| $\Delta\text{FDI}_{fj}$ (dom. sale) | | $-21.93^{***}$ | | | | | |
| | | (6.44) | | | | | |
| Mean dep. var. | 7.84 | 8.69 | 8.69 | 8.69 | 8.69 | 14.77 | 8.88 |
| | *Panel B. Dependent variable: $\Delta$Emp* | | | | | | |
| $\Delta\text{FDI}_{fj}$ | $-16.79^{***}$ | | $-17.75^{***}$ | $-8.72^{*}$ | $-18.28^{***}$ | $-27.46^{***}$ | $-11.56^{***}$ |
| | (4.26) | | (4.26) | (5.12) | (4.17) | (5.17) | (3.54) |
| $\Delta\text{FDI}_{fj}$ (dom. sale) | | $-22.64^{***}$ | | | | | |
| | | (7.53) | | | | | |
| Mean dep. var. | −11.27 | −10.82 | −10.82 | −10.82 | −10.82 | −3.32 | −13.46 |
| NTR gap ctrl. | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| KP-*F* | 112.03 | 17.88 | 92.07 | 39.46 | 148.36 | 115.44 | 165.93 |
| # clusters | 105 | 105 | 105 | 105 | 173 | 110 | 105 |
| N | 949 | 1,017 | 1,017 | 1,017 | 1,017 | 1368 | 1,017 |

**Notes:** Standard errors are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Standard errors are clustered at the SIC 3-digit in columns 1-4 and 6-7 and 4-digit levels in column 5. This table reports the IV estimates of equation (3.3). The FDI exposure $\Delta\text{FDI}_{fj}$ and the IV are defined in equations (3.4) and (3.5), respectively. In Panels A and B, the dependent variables are the DHS growth rates of sales and employment for US firms, respectively. Column 1 excludes all US MNEs that have ever engaged in FDI in China before 2012. Column 2 uses domestic sales to measure FDI exposure, excluding exports. Column 3 constructs the IV using only Japan's FDI in India. Column 4 includes additional controls including China's changes in the domestic FDI policy, log input tariffs, and log output tariffs between 2000 and 2007. Column 5 considers alternative clustering at the 4-digit industry level. Column 6 considers an alternative sample period (1999-2007, pre-Great Recession). Column 7 considers an alternative weight based on initial employment. All specifications include the NTR gap which is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. KP-*F* is the Kleibergen-Papp F-Statistics. Regression models are weighted by initial sales in columns 1-6 and by initial employment in column 7.

# C. Appendix: Theory

## C.1 Additional Expressions

In this subsection, we provide additional expressions for the model.

**Value functions of leaders.** A Home leader's value function (regardless of $m^F > 0$ or not) without JV is expressed as follows:

$$\begin{aligned} r_{Ht} V_{ht}(\mathbf{m};0) - \dot{V}_{ht}(\mathbf{m};0) = \max_{x_{ht}, d_{ht}} \Big\{ & \Pi_{ht}(\mathbf{m}) - \alpha_{Hr} \frac{(x_{ht})^\gamma}{\gamma} w_{Ht} - \alpha_{Hd} \frac{(d_{ht})^\gamma}{\gamma} w_{Ht} \\ & + x_{ht} \Big( V_{ht}(\mathbf{m} + (1,1,0);0) - V_{ht}(\mathbf{m};0) \Big) + x_{ft} \Big( V_{ht}(\mathbf{m} + (-1,0,1);0) - V_{ht}(\mathbf{m};0) \Big) \\ & + d_{ht} \Big( V_{ht}(\mathbf{m};1) - V_{ht}(\mathbf{m};0) - C_t(\mathbf{m}) \Big) \\ & + \sum_{\mathbf{m}'} \tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m}) \Big( V_{ht}(\mathbf{m}';0) - V_{ht}(\mathbf{m};0) \Big) \Big\}, \end{aligned} \tag{C.1}$$

where $\tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m})$ denotes transition probabilities:

$$\tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m}) = \begin{cases} \delta^F & \text{if} \quad \mathbf{m}' = \{0, |m^F| \times \mathbb{1}[m^F \le 0] + m^{DH}, |m^F| \times \mathbb{1}[m^F > 0] + m^{DF}\} \\ \delta^D & \text{if} \quad \mathbf{m}' = \{m^F, 0, m^{DF}\} \\ \delta^D & \text{if} \quad \mathbf{m}' = \{m^F, m^{DH}, 0\} \\ 0 & \text{Otherwise,} \end{cases} \tag{C.2}$$

where $\mathbb{1}[\cdot]$ is an indicator function. By using an indicator function, we generalize equation (4.6) to apply in both cases: $m^F > 0$ and $m^F \le 0$.

A Home leader's value function with JV is

$$\begin{aligned} r_{Ht} V_{ht}(\mathbf{m};1) - \dot{V}_{ht}(\mathbf{m};1) = \max_{x_{ht}} \Big\{ & \Pi_{ht}(\mathbf{m}) - \alpha_{Hr} \frac{(x_{ht})^\gamma}{\gamma} w_{Ht} + \kappa \Pi_{vt}(\mathbf{m}) \\ & + x_{ht} \Big( V_{ht}(\mathbf{m} + (1,1,0);1) - V_{ht}(\mathbf{m};1) \Big) + x_{ft} \Big( V_{ht}(\mathbf{m} + (-1,0,1);1) - V_{ht}(\mathbf{m};1) \Big) \\ & + \phi \Big( V_{ht}(0, |m^F| \times \mathbb{1}[m^F \le 0] + m^{DH}, |m^F| \times \mathbb{1}[m^F > 0] + m^{DF}; 1) - V_{ht}(\mathbf{m};1) \Big) \\ & + \chi \Big( V_{ht}(\mathbf{m};0) - V_{ht}(\mathbf{m};1) \Big) \\ & + \sum_{\mathbf{m}'} \tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m}) \Big( V_{ht}(\mathbf{m}';1) - V_{ht}(\mathbf{m};1) \Big) \Big\}. \end{aligned} \tag{C.3}$$

A Foreign leader's value functions with and without JVs are

$$\begin{aligned}
r_{Ft}V_{ft}(\mathbf{m};0) - \dot{V}_{ft}(\mathbf{m};0) = \max_{x_{ft}} \Big\{ & \Pi_{ft}(\mathbf{m}) - \alpha_{Fr}\frac{(x_{ft})^{\gamma}}{\gamma}w_{Ft} \\
& + x_{ft}\Big(V_{ft}(\mathbf{m}+(-1,0,1);0) - V_{ft}(\mathbf{m};0)\Big) + x_{ht}\Big(V_{ft}(\mathbf{m}+(1,1,0);0) - V_{ft}(\mathbf{m};0)\Big) \\
& + d_{ht}\Big(V_{ft}(\mathbf{m};1) - V_{ft}(\mathbf{m};0) + C_t(\mathbf{m})\Big) \\
& + \sum_{\mathbf{m}'} \tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m})\Big(V_{ft}(\mathbf{m}';0) - V_{ft}(\mathbf{m};0)\Big)\Big\}.
\end{aligned} \tag{C.4}$$

$$\begin{aligned}
r_{Ft}V_{ft}(\mathbf{m};1) - \dot{V}_{ft}(\mathbf{m};1) = \max_{x_{ft}} \Big\{ & \Pi_{ft}(\mathbf{m}) - \alpha_{Fr}\frac{(x_{ft})^{\gamma}}{\gamma}w_{Ht} + (1-\kappa)\Pi_{vt}(\mathbf{m}) \\
& + x_{ft}\Big(V_{ft}(\mathbf{m}+(-1,0,1);1) - V_{ft}(\mathbf{m};1)\Big) + x_{ht}\Big(V_{ft}(\mathbf{m}+(1,1,0);1) - V_{ft}(\mathbf{m};1)\Big) \\
& + \phi\Big(V_{ft}(0,|m^F| \times \mathbb{1}[m^F \leq 0] + m^{DH}, |m^F| \times \mathbb{1}[m^F > 0] + m^{DF};1) - V_{ft}(\mathbf{m};1)\Big) \\
& + \chi\Big(V_{ft}(\mathbf{m};0) - V_{ft}(\mathbf{m};1)\Big) \\
& + \sum_{\mathbf{m}'} \tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m})\Big(V_{ft}(\mathbf{m}';1) - V_{ft}(\mathbf{m};1)\Big)\Big\}.
\end{aligned} \tag{C.5}$$

**Value functions of fringe firms.** For both fringe firms in Home and Foreign, $i \in \{\tilde{h}, \tilde{f}\}$, the value functions without and with JVs are expressed as follows:

$$\begin{aligned}
r_{ct}V_{it}(\mathbf{m};0) - \dot{V}_{it}(\mathbf{m};0) = \; & \Pi_{it}(\mathbf{m}) \\
& + x_{ht}\Big(V_{it}(\mathbf{m}+(1,1,0);0) - V_{it}(\mathbf{m};0)\Big) + x_{ft}\Big(V_{it}(\mathbf{m}+(-1,0,1);0) - V_{it}(\mathbf{m};0)\Big) \\
& + d_{ht}\Big(V_{it}(\mathbf{m};1) - V_{it}(\mathbf{m};0\Big) \\
& + \sum_{\mathbf{m}'} \tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m})\Big(V_{it}(\mathbf{m}';0) - V_{it}(\mathbf{m};0)\Big).
\end{aligned} \tag{C.6}$$

$$\begin{aligned}
r_{ct}V_{it}(\mathbf{m};1) - \dot{V}_{it}(\mathbf{m};1) = \; & \Pi_{it}(\mathbf{m}) \\
& + x_{ft}\Big(V_{it}(\mathbf{m}+(-1,0,1);1) - V_{it}(\mathbf{m};1)\Big) + x_{ht}\Big(V_{it}(\mathbf{m}+(1,1,0);1) - V_{it}(\mathbf{m};1)\Big) \\
& + \phi\Big(V_{it}(0,|m^F| \times \mathbb{1}[m^F \leq 0] + m^{DH}, |m^F| \times \mathbb{1}[m^F > 0] + m^{DF};1) - V_{it}(\mathbf{m};1)\Big) \\
& + \chi\Big(V_{it}(\mathbf{m};0) - V_{it}(\mathbf{m};1)\Big) \\
& + \sum_{\mathbf{m}'} \tilde{\mathbb{T}}(\mathbf{m}';\mathbf{m})\Big(V_{it}(\mathbf{m}';1) - V_{it}(\mathbf{m};1)\Big)\Big\}.
\end{aligned} \tag{C.7}$$

**Law of motion for distribution of technology gap and JV status.** The law of motion for $\mu_t(\mathbf{m};\mathcal{J})$ over states $\mathbf{m}$ and $\mathcal{J}$ is

$$\begin{aligned}
\dot{\mu}_t(\mathbf{m};\mathcal{J}) = & \underbrace{x_{ht}(m^F-1,m^{DH}-1,m^{DF};\mathcal{J})\mu_t(m^F-1,m^{DH}-1,m^{DF};\mathcal{J})}_{\text{Innovation by Home leader}} \\
& + \underbrace{x_{ft}(m^F+1,m^{DH},m^{DF}-1;\mathcal{J})\mu_t(m^F+1,m^{DH},m^{DF}-1;\mathcal{J})}_{\text{Innovation by Foreign leader}} \\
& + \underbrace{d_{ht}(m^F,m^{DH},m^{DF};0)\mathbb{1}[\mathcal{J}=1]\mu_t(m^F,m^{DH},m^{DF};0)}_{\text{JV investment}} + \underbrace{\chi\mathbb{1}[\mathcal{J}=0]\mu_t(m^F,m^{DH},m^{DF};1)}_{\text{JV exit}} \\
& + \underbrace{\delta^D\mathbb{1}[m^{DH}=0]}_{\text{Home within-country diffusion}} + \underbrace{\delta^D\mathbb{1}[m^{DF}=0]}_{\text{Foreign within-country diffusion}} + \underbrace{\delta^F\mathbb{1}[m^F=0,\mathcal{J}=0]}_{\text{Across-country diffusion}} + \underbrace{\phi\mathbb{1}[m^F=0,\mathcal{J}=1]}_{\text{JV direct diffusion}} \\
& - \underbrace{\left(x_{ht}(\mathbf{m};\mathcal{J})+x_{Ft}(\mathbf{m};\mathcal{J})+2*\delta^D+\delta^F+\phi\right)\mu_t(\mathbf{m};\mathcal{J})}_{\text{Subtracted mass}}.
\end{aligned} \tag{C.8}$$

The first four lines of the right hand side capture the mass that enters a state $(\mathbb{m};\mathcal{J})$ from other states. The first line captures that in state $(m^F-1,m^{DH}-1,m^{DF})$, Home leader's successful innovation moves to $(m^F,m^{DH}.m^{DF})$ with intensity $x_{ht}$. The second line captures evolution of states due to Foreign leader's innovation. In the third line, $\mathbb{1}[\mathcal{J}=1]$ or $\mathbb{1}[\mathcal{J}=0]$ are indicator functions of the JV status. For $\mathcal{J}=1$, with intensity $d_{ht}$, a JV is established moving from a state $(m^F,m^{DH}.m^{DF};0)$ to state $(m^F,m^{DH}.m^{DF};1)$. The second term in the third line captures the exogenous exit of existing JVs when $\mathcal{J}=1$. The fourth line captures evolution of states due to direct diffusion through JVs, within-country and across-country spillovers. Finally, the last line captures the mass leaving the current state.

# D. Appendix: Quantitative Exercise

## D.1 Mapping Model Objects to the Estimated Coefficients from the Data

**Direct effects on Chinese partners in Fact 1.** For Chinese leaders and fringe firms, we run the following regression model which is analogous to equation (3.1) using OLS:

$$\ln \text{Sale}_{ijt} = \beta\mathbb{1}[\text{Post-JV}_{it}] + \delta_i + \delta_{jt} + \varepsilon_{ijt}, \qquad i \in \{f, \tilde{f}\}$$

where $i$ denotes firm and $t$ periods. $\delta_i$ is firm time-invariant fixed effects, and $\delta_{jt}$ is product-year fixed effects. $\mathbb{1}[\text{Post-JV}_{it}]$ is a dummy which equals 1 for periods after firm $i$ forms JVs.

**Sectoral regressions in Facts 2 and 3.** To estimate the model, we replicate the sector-level regressions of facts 2 and 3 in Section 3. We simulate 100,000 products in the model, whose technology gap between US and China is randomly drawn from the calibrated normal distribution. Each product corresponds to each sector. However, since innovation and diffusion are stochastic, sectors become heterogeneous over time in terms of their technology gap relative to other firms. We then estimate Equations (3.3) and (3.6), with two key differences.

In the model, we run the following sectoral regression analogous to equation (3.3) using OLS:

$$\Delta \text{Sale}_{hj} = \beta \Delta \text{JV}_j + \delta_{m^F,99} + \varepsilon_{jm}, \tag{D.1}$$

where $h$ denotes US leaders $j$ products. The dependent variable is DHS growth of US leaders' sales. $\delta_{m^F,99}$ are fixed effects for the initial US-China gap $m^F \in \{-\bar{m}, \ldots, \bar{m}\}$ in 1999. Multiple products with the same initial gap identify these fixed effects. We abstract away from additional controls used in the empirical analysis, because it is difficult to define the additional controls in the model (e.g., NTR gap).

$\Delta \text{JV}_j$ is defined analogously to the FDI exposure defined in equation (3.4), with one modification:

$$\Delta \text{JV}_j = \frac{\text{Avg. JV sales in China}_{j,99-12}}{\text{Total sales in China}_{j,99}} - \frac{\text{JV sales in China}_{j,99}}{\text{Total sales in China}_{j,99}}. \tag{D.2}$$

The modification is that, unlike equation (3.4), we use the average JV sales between 1999 and 2012, instead of the last value in 2012 due to mean reversion. In the model, JVs exit with an exogenous probability. Therefore, products (or sectors) initially with JVs are likely to lose JVs due to these exogenous exit in 2012. These exogenous exits lead to changes in JV sales shares between 1999 and 2012 to take negative values due to this mean reversion, which is an artifact of the model. Despite this exit, however, Chinese firms in that sector may have already benefited from knowledge diffusion, increasing their market share in the US. To account for this, we use the average sales share of JV firms.

For the non-targeted moment on the relationship between R&D and the JV exposure, we run the above regression with DHS growth of firms' R&D expenditures as the dependent variable.

## D.2 Nash-in-Nash Bargaining

We adopt the Nash-in-Nash solution, where each negotiating pair maximizes its Nash product, taking the actions of other pairs as given.

$$\begin{aligned} C_t(\mathbf{m}) &= \underset{C}{\operatorname{argmax}} \left\{ \left(\Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C - C^E\right)^{\xi} \times \left(\Delta^{\text{JV}} V_{ft}(\mathbf{m}) + C\right)^{1-\xi} \right\} \\ &\text{s.t.} \qquad \Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C - C^E \geq 0, \qquad \Delta^{\text{JV}} V_{ft}(\mathbf{m}) + C \geq 0 \\ &= (1-\xi)\left(\Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C^E\right) - \xi \Delta^{\text{JV}} V_{ft}(\mathbf{m}) \end{aligned} \tag{D.3}$$

$$\begin{aligned} C_t^E(\mathbf{m}) &= \underset{C}{\operatorname{argmax}} \left\{ \left(\Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C - C^E\right)^{\xi^E} \times \left(\Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m}) + C^E\right)^{1-\xi^E} \right\} \\ &\text{s.t.} \qquad \Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C - C^E \geq 0, \qquad \Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m}) + C^E \geq 0 \\ &= (1-\xi^E)\left(\Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C\right) - \xi^E \Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m}) \end{aligned} \tag{D.4}$$

Combining equations (D.3) and (D.4), we obtain

$$C = \frac{\xi^E(1-\xi)}{\xi^E(1-\xi)+\xi}\left\{\Delta^{\mathrm{JV}}V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}}V_{\tilde{h}t}(\mathbf{m})\right\} - \frac{\xi}{\xi^E(1-\xi)+\xi}\Delta^{\mathrm{JV}}V_{ft}(\mathbf{m}) \tag{D.5}$$

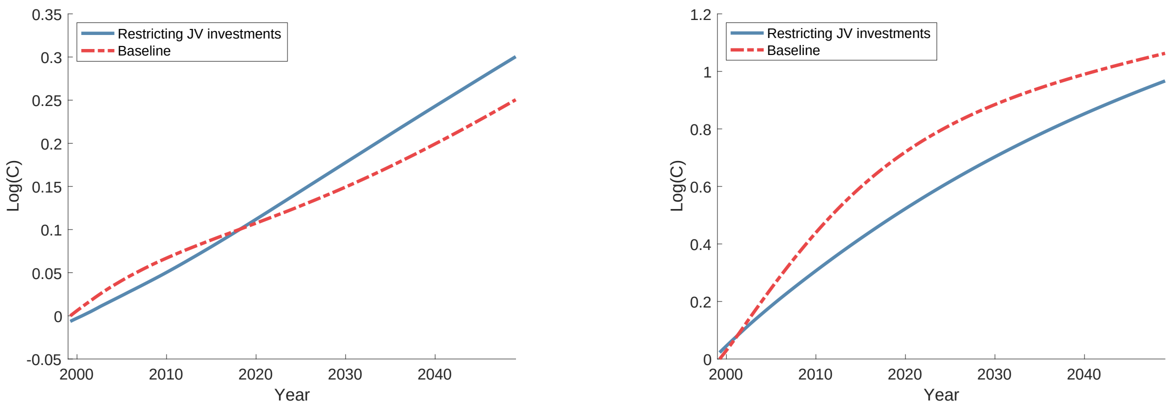
$$C^E = \frac{\xi(1-\xi^E)}{\xi(1-\xi^E)+\xi^E}\left\{\Delta^{\mathrm{JV}}V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}}V_{ft}(\mathbf{m})\right\} - \frac{\xi^E}{\xi(1-\xi^E)+\xi^E}\Delta^{\mathrm{JV}}V_{\tilde{h}t}(\mathbf{m}). \tag{D.6}$$

When we set $\xi^E = 1$, the above expressions collapse to

$$C = (1-\xi)\left\{\Delta^{\mathrm{JV}}V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}}V_{\tilde{h}t}(\mathbf{m})\right\} - \xi\Delta^{\mathrm{JV}}V_{ft}(\mathbf{m}), \qquad C^E = -\Delta^{\mathrm{JV}}V_{\tilde{h}t}(\mathbf{m}). \tag{D.7}$$

## D.3 Additional Figures and Tables

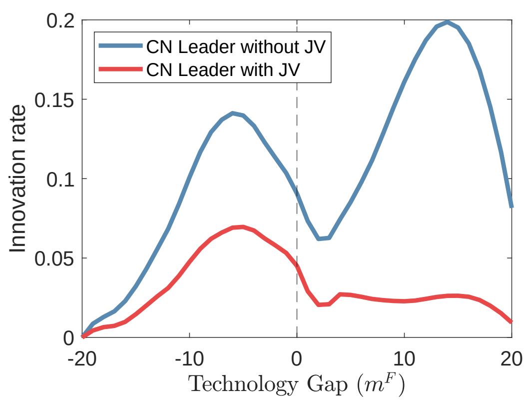
Figure D1: Baseline vs. Restricting Joint Venture Investments. Path of Log Consumption




A. US B. China

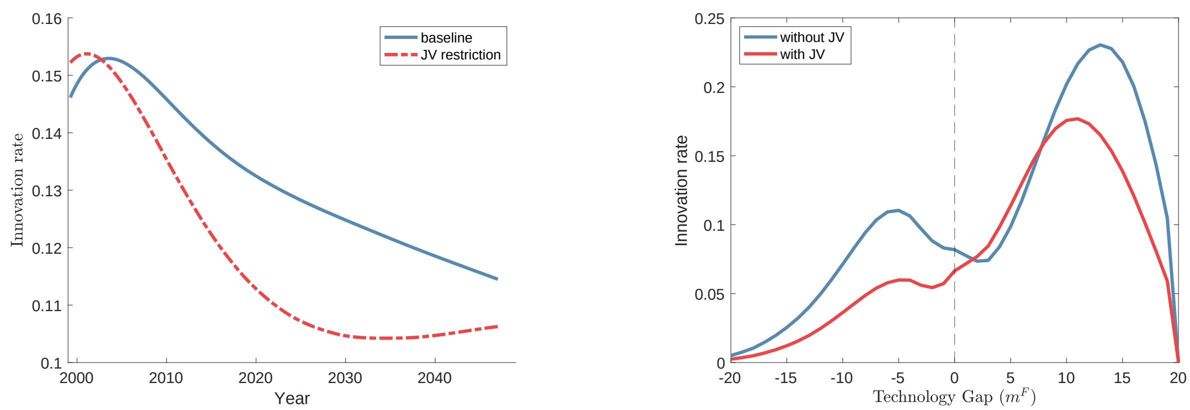
***Notes.*** This figure presents log consumption of the US and China when restricting JV investments along with the baseline scenario.

Figure D2: China Innovation Rate over Technology Gap



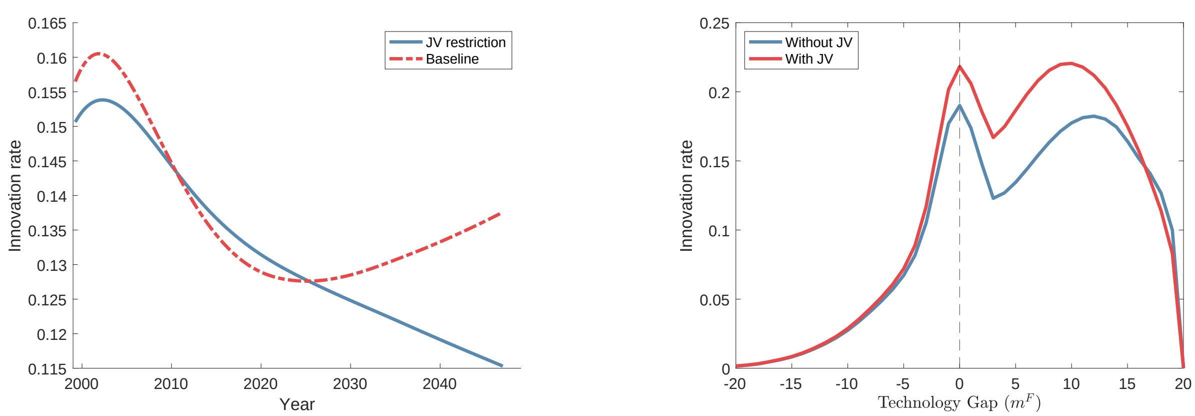

***Notes.*** This figure plots the innovation rate in the baseline scenario in 2025 over $m^F$, technology gap between US and Chinese leader firms. $m^F > 0$ denotes the case where US leaders have higher productivity than Chinese leaders. Technology gaps between domestic firms are set to $m^{DF} = m^{DH} = \bar{m}$.

Figure D3: US Innovation Rate over Time and Technology Gap. The Cases of Larger Market Size $\kappa = 1$ and No Direct Diffusion $\phi = 0$




Larger market size effect ($\kappa = 1$)

A. US average innovation rate ($\kappa = 1$) B. US Innovation rate over technology gap ($\kappa = 1$)

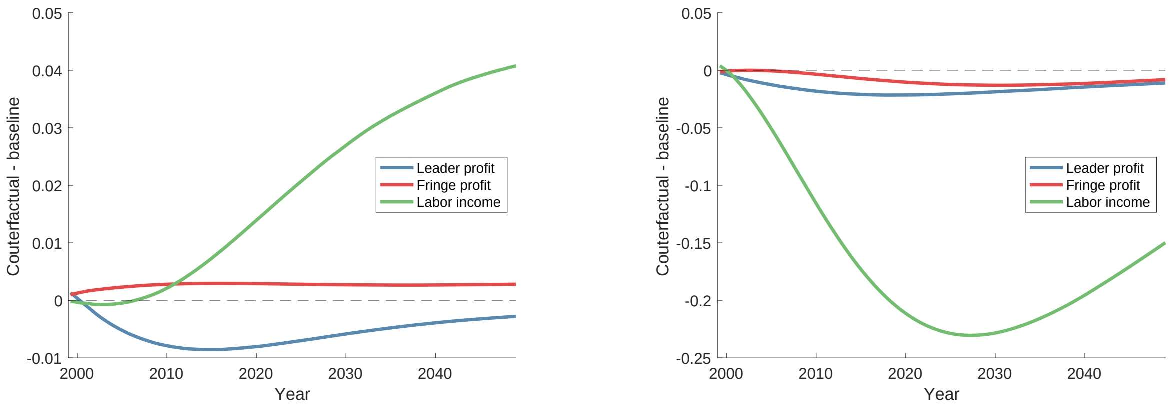



No direct diffusion ($\phi = 0$)

C. US average innovation rate ($\phi = 0$) D. US Innovation rate over technology gap ($\phi = 0$)

***Notes.*** In Panels A and B, we consider the case of larger market size effects by setting $\kappa = 1$. In Panels C and D, we shut down direct diffusion by setting $\phi = 0$. Panels A and C plot the average innovation rate in baseline and counterfactual scenarios. Panels B and D plots the innovation rate in the baseline scenario in 2025 over $m^F$, technology gap between US and Chinese leader firms. $m^F > 0$ denotes the case when US firms exceed the Chinese leader in productivity. In this example, technology gaps between domestic firms are set to $m^{DF} = m^{DH} = \bar{m}$.

Figure D4: Baseline vs. Restricting Joint Venture Investments in 1999: Dynamics of Real Profits and Labor Income




A. US B. CN

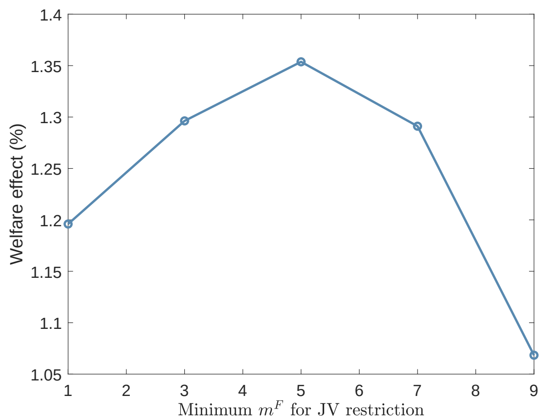
***Notes.*** This figure plots the difference between the variables in the counterfactual, where JV investments are forbidden, and those in the baseline scenario. Panel A shows the results for the US, while Panel B displays the results for China. Leader profit includes the profits of leader firms and the share of profits from JV firms. All variables are deflated by each country's price index.

Table D1: Baseline vs. Restricting Joint Venture in 1999. Robustness. Sensitivity Checks

| | Δ US Welfare (%) | ΔCN Welfare (%) | Δ US Innovation rate (%) | Δ CN Innovation rate (%) |
|---|---|---|---|---|
| Baseline | 1.28 | −10.26 | 1.61 | 7.70 |
| | *Panel B. Direct diffusion (baseline: $\phi = 0.150$)* | | | |
| $\phi = 0.125$ | 1.25 | −10.39 | 1.44 | 7.89 |
| $\phi = 0.175$ | 1.28 | −10.06 | 1.74 | 7.49 |
| | *Panel C. Across-country diffusion (baseline: $\delta^F = 0.024$)* | | | |
| $\delta^F = 0.019$ | 0.70 | −10.08 | 1.60 | 7.56 |
| $\delta^F = 0.029$ | 1.37 | −9.41 | 1.48 | 6.98 |
| | *Panel D. Within-country diffusion (baseline: $\delta^D = 0.027$)* | | | |
| $\delta^D = 0.022$ | 1.41 | −10.11 | 1.71 | 7.86 |
| $\delta^D = 0.032$ | 1.19 | −10.38 | 1.51 | 7.55 |
| | *Panel E. Initial technology gap (baseline: $\mathcal{D} = 20$)* | | | |
| $\mathcal{D} = 23$ | 1.69 | −10.96 | 1.31 | 7.10 |
| $\mathcal{D} = 17$ | 0.68 | −9.51 | 1.54 | 7.93 |
| | *Panel F. US JV profit share (baseline: $\kappa = 0.54$)* | | | |
| $\kappa = 0.75$ | 0.97 | −10.89 | 1.48 | 7.64 |
| $\kappa = 0.25$ | 1.67 | −9.51 | 1.78 | 7.72 |

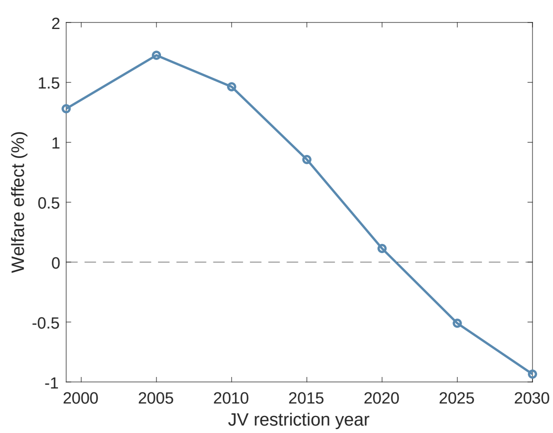
***Notes.*** This table reports the effects of restricting JV in 1999 with alternative parameterizations. Δ Welfare is expressed in consumption-equivalent units, and Δ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

Figure D5: Baseline vs. Restricting Joint Venture Investments in 1999 Conditional on Different Technology Gaps. Welfare Effects (%)




***Notes.*** This figure reports US consmption-equivalent welfare changes from restricting JV investments conditional on different minimum technology gaps, compared to the baseline scenario. The x-axis denotes for technology gaps above which JVs are prohibited.

Figure D6: Baseline vs. Restricting Joint Venture Investments over Different Years. Welfare Effects (%)




***Notes.*** This figure reports consmption-equivalent welfare changes of the US from restricting JV investments in different years, compared to the baseline scenario. The x-axis denotes for years in which JV investments are restricted.