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 1.2 percent but reduced China's by 10.3 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

[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).

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 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. We regress growth of measures of firm size and productivity. In sectors with more joint ventures, these firms tended to grow larger and more technologically advanced. Last but most important, we find that in sectors with more joint ventures, US firms experienced negative effects on their size and innovation.

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 use 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 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 form a joint venture makes US leaders innovate more, because their innovation increases profits from the 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.

In the model, 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 US firms from forming JVs with Chinese firms from 1999, the beginning of our dataset. We find that prohibiting joint ventures increases US welfare by 1.2 percent in units of permanent consumption. For the US, leaders' profits fall by 22 percent in present value terms, while fringe firms' profits increase by 4.9 percent; however, total profits decline. Yet, the real wage increases by 2.9 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 10.3 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). Our model builds on Akcigit et al. (2023) and Choi and Shim (2024), where firms compete with foreign firms through innovation but also benefit 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., 2015). 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

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

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. 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; Cai and Xiang, 2025). 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. (2015). 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 knowledge diffusion through FDI. 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 in line 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 negative competition effects of US MNEs' joint ventures on other US firms.

[4]For example, see Javorcik (2004); Keller and Yeaple (2009); Lu et al. (2017); Alfaro and Chen (2018); Setzler and Tintelnot (2021); Alfaro-Ureña et al. (2022); Gong (2023); Choi and Shim (2025) for spillovers from FDI or technology transfers.

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" (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).[5] 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. Despite these post-WTO reforms, the quid pro quo policy has been at the center of US–China tensions. US policymakers have criticized it as an unfair trade practice and argue that it has persisted in more implicit forms.[6]

[5]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."*

[6]In its 2017–18 Section 301 investigations, the Office of the United States Trade Representative reported that

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 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. 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 it with the Chinese Customs Trade Statistics from 2000 to 2013, which 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.[7] 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 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 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

China implicitly pressured foreign MNEs to form JVs and transfer advanced technologies through both formal regulations and informal administrative barriers.

[7] 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.

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. 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 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. We construct firm-level counts of yearly new patents and 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).

3. Motivating Facts

In this section, we present three motivating facts on JVs.

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.

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).

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

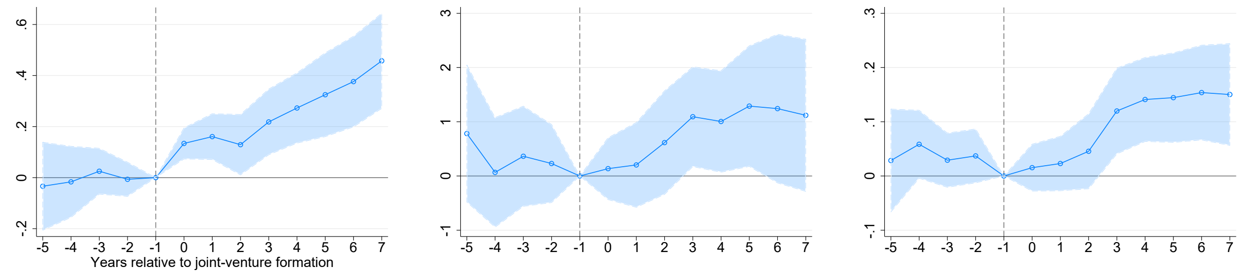
$$y_{imt} = \sum_{\tau=-5}^{7} \beta_\tau \Big(D_{mt}^{\tau} \times \mathbb{1}[\text{JV Partner}_{it}] \Big) + \delta_{im} + \delta_{mt} + \varepsilon_{imt} \tag{3.1}$$

where i denotes firm, m match, and t year. D_{mt}^{τ} 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 β_{-1} to zero. δ_{im} and δ_{mt} are match-firm and match-year fixed effects. ε_{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

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



A. Log sale B. Ihs export C. 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. β_{-1} is normalized to zero. In Panels A, B, and C, the dependent variables are log sales, inverse hyperbolic sine transformation of exports, and technological proximity (equation (3.2)).

using patent data, as patents reflect their technological capabilities[8]:

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

$F_{imt} = (p_{i1t}, \ldots, p_{iKt})^{\top}$ 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.[9] Similarly, $F_{\text{MNE}(i),t(m)}$ represents foreign MNEs' patent stock from the USPTO, measured at the event year $t(m)$, making it fixed over time. Because $F_{\text{MNE}(i),t(m)}$ 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.

Figure 1 reports the results (see cols. 1-4 of Appendix Table B3 for more details). 4

[8] 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 resulted in 176 matches with 176 and 692 unique treated and control group firms.

[9] 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 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. Similar measures have been used in prior studies (e.g. Branstetter, 2006; Bloom et al., 2013; Akcigit et al., 2016).

years after forming JVs for the first time, Chinese partners' sales and capital increased by 27% and 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. Forming JVs also had positive impacts on log employment, export dummies, cumulative patents and yearly new patents (cols. 5-8 of Appendix Table B3).

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 Δy_{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. ε_{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. $\Delta\mathrm{FDI}_{fj}$ 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:

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

where $\mathcal{J}^{\mathrm{CN}}_{(-f)jt}$ is a set of sector j FDI affiliates in China in year t.[10] We focus on total FDI rather than separating JVs and WFOEs because the only difference between WFOEs and JVs is whether Chinese partner firms are involved or not. However, as long as WFOEs

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

Table 1: OLS. Indirect Positive Spillovers to Chinese Firms

Dep. var.	ΔSale		ΔEmp.		ΔCapital		ΔExport		ΔPatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔFDI_{fj}	8.97***	7.51***	7.30***	7.31***	8.89***	7.28***	19.91***	16.45***	2.53***	1.88***
	(1.73)	(2.03)	(1.40)	(1.53)	(1.79)	(1.82)	(3.37)	(2.95)	(0.87)	(0.56)
NTRgap_j	−0.08	0.11	0.55*	0.66***	0.15	0.20	1.28*	1.01	0.55**	0.37*
	(0.32)	(0.34)	(0.29)	(0.25)	(0.29)	(0.28)	(0.73)	(0.62)	(0.28)	(0.22)
Add. ctrl.		✓		✓		✓		✓		✓
Mean dep. var.	79.61	79.61	−7.08	−7.08	38.83	38.83	50.60	50.60	172.28	172.28
# clusters	157	157	157	157	157	157	155	155	155	155
N	14844	14844	14844	14844	14844	14844	8491	8491	6628	6628

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 estimates of equation (3.3). ΔFDI_{fj} is defined in equation (3.4). In columns 1-2, 3-4, 5-6, 7-8, and 9-10, the dependent variables are the DHS growth rates of sales, employment, capital, exports, and cumulative patents 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, 1993 US production worker shares, 1990 US computer and high-tech investment shares, and 1-digit industry dummies. All regression models are weighted by initial sales.

generate indirect spillovers, they can also lead to the negative externality because MNEs fail to internalize other firms' profit losses through these spillovers. 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 that share the same Chinese parents.

To isolate effects of the FDI exposure from changes in trade policies post-WTO, we include 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).[11]

Table 1 presents the results. In column 1, the dependent variable is sales growth. OLS estimates are positive and statistically significant at the 1% level. A 1 percentage point increase in the FDI exposure is associated with an 0.09 percentage point higher sales growth. In Column 2, we additionally control for sectoral technological trends and include 1-digit industry

[11] NTRgap_j is 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. We obtain the SIC 4-digit level NTR gap from Che et al. (2022). It has been well-documented that such reductions measured by the NTR gap contributed to declines in US manufacturing (Pierce and Schott, 2016).

dummies to absorb technological factors that may influence FDI.[12] The coefficients remain stable within one standard error of the estimate. In columns 3-10, the FDI exposure also had positive effects on growths of employment, capital, exports, and cumulative patents.[13] The NTR gap had positive effects on Chinese firms, although these estimates are less precise.

We further provide evidence that these improvements were associated with improvements in their quality and productivity. The FDI exposure is also positively correlated with various proxies for productivity, including DHS growth of the number of exporting/importing products/countries between 2000 and 2013, obtained from the Chinese customs data; growth of wages per employment, a proxy for workers' skills; and dummies of receiving "high-tech" certificate from the government (Appendix Table B4).

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.3, 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 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 (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. Negative Competition Effects to US Firms

In this subsection, we examine the negative competition effects to US firms. We show that higher FDI exposure was associated with the decline of US manufacturing. We run the same OLS long-difference regression for US firms between 1999-2012. For US firms, the FDI exposure is defined at the SIC 4 digit levels. Standard errors are clustered at the SIC-3 digit level. 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 intensify competition in the global market. When constructing the FDI exposure, for each US MNE, Chinese FDI affiliates

[12] These controls include 1996 US import penetration, 1993 production worker shares, 1990 computer and high-tech investment shares, and 1-digit industry dummies.

[13] The sample size decreases for export and patent outcomes, 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 2: Negative Competition Effects to US Firms

Dep. var.	ΔSale		ΔEmp.		ΔCapital		ΔExport		ΔR&D		ΔPatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔFDI_{fj}	-11.08^{***}	-10.65^{***}	-10.65^{***}	-9.28^{***}	-12.90^{***}	-10.83^{***}	-7.97^{*}	-10.20^{***}	-10.53^{**}	-9.48^{***}	-1.21	-1.30
	(2.95)	(1.62)	(3.33)	(2.04)	(2.76)	(2.51)	(4.21)	(2.94)	(4.25)	(2.67)	(1.56)	(1.76)
NTRgap_j	-1.10	-1.39^{**}	-1.01	-1.50^{**}	-0.87	-1.34^{*}	-1.49	-2.04	-1.45	-2.05^{***}	0.63	0.46
	(0.78)	(0.65)	(0.91)	(0.75)	(0.89)	(0.73)	(1.37)	(1.35)	(0.89)	(0.63)	(0.43)	(0.44)
Controls		✓		✓		✓		✓		✓		✓
Mean dep. var.	8.69	8.69	−10.82	−10.82	0.52	0.52	35.91	35.91	6.33	6.33	65.94	65.94
# clusters	105	105	105	105	105	105	101	101	80	80	100	100
N	1017	1017	1017	1017	1017	1017	834	834	525	525	837	837

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 of equation (3.3). ΔFDI_{fj} is defined in equations (3.4). 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. 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 the same set of additional controls in Table 1. All regression models are weighted by initial sales.

associated with it are excluded from the numerator.

Table 2 reports the results. Column 1 reports the estimate for sales growth, which is significantly negative at the 1% level. The estimate implies that a 1 percentage point increase in the FDI exposure is associated with a 0.11 percentage point lower sales growth. The result remains stable with the additional controls in column 2. The FDI exposure was also negatively correlated with employment, capital, and export growth and innovation outcomes including growth of R&D and the number of cumulative patents. These innovation results are consistent with Autor et al. (2020) who found the negative impacts of the China shock on US firms' innovation outcomes. The FDI exposure not only negatively affected US firms but also firms in other countries, further supporting the increased global competition due to FDI (Appendix Table B5).

Alternative IV Strategy and robustness checks. The OLS estimates for spillovers and competition effects may suffer from endogeneity. To alleviate this concern, we consider two IV strategies. First, we use sectoral changes in FDI by South Korean and Japanese MNEs in India as an IV. This exploits push factors driving these countries' FDI into China, which are arguably exogenous to US- and China-specific factors. Second, we use changes in sector-level indicators for being subject the FDI regulation based on the Catalogue for the Guidance of

Foreign Investment Industries over 1998-2007, an approach first proposed by Lu et al. (2017), who also used this IV to instrument sectoral FDI exposure.[14] Appendix B.2 discusses these two strategies and their identifying assumptions in detail. The IV estimates are larger in magnitude than the OLS estimates.

We also conduct additional robustness checks for Facts 2 and 3. The results remain robust to clustering at the 4-digit industry level, restricting the sample to 1999–2007 (pre–Great Recession), and using employment-based weights. These results are reported in Appendix Table B6.

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.

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 τ^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

[14] Since 1995, the Catalogue has provided guidelines for FDI regulations, which were gradually relaxed with revisions in 1997, 2002, 2004, and 2007. 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. The policy change data come from Brandt et al. (2017).

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,

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

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_{Ht}^T and C_{Ht}^N):

$$C_{Ht} = (C_{Ht}^T)^\beta (C_{Ht}^N)^{1-\beta}, \qquad P_{Ht} = \left(\frac{P_{Ht}^T}{\beta}\right)^\beta \left(\frac{P_{Ht}^N}{1-\beta}\right)^{1-\beta} \tag{4.2}$$

where β denotes the expenditure share on the tradable sector, and P_{Ht}^T and P_{Ht}^N denote the price indices of tradable and non-tradable sectoral outputs, respectively.

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. ψ_i is a demand shifter for each firm. Leaders in both countries and the JV have the same parameter value (ψ =

$\psi_h = \psi_f = \psi_v$), 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 the introduction of 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 $\mathcal{I}_{jt} = |\mathcal{I}_H \bigcup \mathcal{I}_{Fjt}|$. In the quantitative section, we also present results under the assumption that the love of variety is preserved. 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.

A sectoral good in the non-tradable sector is produced by a perfectly-competitive representative firm. Its production function is linear in labor: $C_{Ht}^N = Z_{Ht}^N L_{Ht}^N$, where Z_{Ht}^N is exogenous productivity, which grows at rate g^{NT}. With perfect competition, $P_{Ht}^N = \frac{w_{Ht}}{Z_{Ht}^N}$.

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 and 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

$$p_{hjt} = \frac{1 - \frac{\sigma-1}{\sigma} s_{hjt}}{\frac{\sigma-1}{\sigma}(1 - s_{hjt})} \frac{w_{Ht}}{z_{hjt}} \quad \text{and} \quad p_{hjt}^* = \frac{1 - \frac{\sigma-1}{\sigma} s_{hjt}^*}{\frac{\sigma-1}{\sigma}(1 - s_{hjt}^*)} \frac{\tau^x w_{Ht}}{z_{hjt}}, \tag{4.3}$$

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

$$\pi_{hjt} = \frac{s_{hjt}}{\sigma - (\sigma-1) s_{hjt}} P_{Ht}^T C_{Ht}^T \quad \text{and} \quad \pi_{hjt}^* = \frac{s_{hjt}^*}{\sigma - (\sigma-1) s_{hjt}^*} P_{Ft}^T C_{Ft}^T. \tag{4.4}$$

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. They choose the Poisson arrival rate of innovation, x_{ijt}, subject to 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 α_{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 $z_{ij,t+\Delta t} = \lambda \times z_{ijt}$, where $\lambda > 1$ denotes the step size of productivity improvement.

Fringe firms do not innovate. Their productivity improves only via knowledge diffusion from domestic leaders.

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.[15] 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).

The JV firm's 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.[16]

We assume that JVs maximize their own profits rather than jointly optimizing total profits

[15] 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).

[16] 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.

with their parent firms.[17] A Home leader receives a κ share of the JV's total profits Π_{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 the Poisson arrival 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 α_{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.[18] 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.[19] Once established, a JV operates until it exits exogenously at rate χ.

Knowledge diffusion. There are three types of knowledge diffusion. First is direct diffusion from JVs. While operating, the lagging partner (Home or Foreign) directly learns from its more advanced partner, catching up to that partner's productivity at rate ϕ, capturing fact 1. The second is within-country knowledge diffusion. Fringe firms catch up with the leader's productivity level at rate δ^D.[20] JVs also indirectly benefit Foreign fringe firms through this within-country diffusion, as in 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 fact 3.

[17]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.

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

[19]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 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.

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

The third is across-country diffusion. With a rate of δ^F, a lagged leader catches up to the productivity with an advanced foreign leader. δ^F captures knowledge diffusion across countries through channels other than JVs.[21]

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

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

$m^F_{jt} \equiv N_{hjt} - N_{fjt} \in \{-\bar{m}, \ldots, 0, \ldots, \bar{m}\}$ 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. Because products are symmetric, we drop all subscripts of $\mathbf{m}_{jt}$ and sector-specific subscripts 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., $m^F > 0$). The value functions for other cases are provided in Appendix C.

[21] For example, see Buera and Oberfield (2020) and de Souza et al. (2025) for knowledge diffusion through international trade, and Santacreu (2024) and Choi and Shim (2024) for diffusion via formal licensing.

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

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

where $\mathbb{T}(\mathbf{m}';\mathbf{m})$ denotes transition probabilities from $\mathbf{m}$ to $\mathbf{m}'$ due to knowledge diffusion as:

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

The first line of the right-hand-side in equation (4.6) represents static profits (operating profits net of innovation and JV formation costs). The second line reflects the value changes due to own innovation and a Foreign leader's innovation. The first term of third line reflects value changes due to forming a JV. The second term of the same line reflect value changes due to exogenous spillovers.

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

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

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

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

Joint venture fee. With a successful JV formation rate 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 ξ is the bargaining power of Home leaders and Δ^{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 lag further 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., $C_t(\mathbf{m}) \leq 0$). 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. This creates a negative competition externality and may lead to over-investment in JVs from the US perspective. Similarly, Foreign leaders do not internalize knowledge diffusion to Foreign fringe firms, which can lead to underinvestment in JVs from the Chinese perspective.

Combining Equation (4.9) and (4.10), 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 ξ. The total surplus from JV increases with the technology gap, because JV profits and Chinese rivals' productivity gains from diffusion increase with the gap.

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 Home firms. Goods markets clear:

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

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.

The balance of payment equation is as below:

$$\int_0^1 \left(\sum_{i \in \mathcal{I}_{Fjt}} p^*_{ijt} y^*_{ijt} + d_{hjt} C_{jt} \right) dj = \int_0^1 \left(\sum_{i \in \mathcal{I}_H} p^*_{ijt} y^*_{ijt} + \kappa \Pi_{vjt} \right) dj\ ,$$

where the sum of imports and JV fee payments equals the sum of exports and the share of JV profits distributed to Home leaders.

Equilibrium. The distribution over states $\mu_t(\mathbf{m}; \mathcal{J})$ evolves endogenously according to firms' optimal innovation and JV decisions. Its law of 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

Market failures. 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 (ϕ,δ^D), and leaders' demand shifters, ψ, govern the magnitude of this externality. Higher diffusion rate intensifies 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. At the same time, it produces business stealing effects that may lead to over-investment in innovation. Oligopolistic market power causes firms to produce below socially optimal levels.

The two country assumption. Our model builds on a two-country framework to focus on strategic interactions between firms while maintaining computational feasibility. Under this assumption, with the US is the sole source of foreign technology for China. One concern is that this may exaggerate the role of US JVs. If we were to include a third country, such as Japan, China could substitute away from the US and rely on Japanese JVs when US JVs are restricted. However, strategic interactions could also emerge between the US and Japan. Competing foreign firms may race to transfer technologies to China, knowing that their own technology's value could decline if a rival country transfers it first, creating a "prisoner's dilemma." In this case, the US ban on JV investments could also reduce the incentive for Japanese firms to engage in JVs with China, as the strategic pressure to transfer technology weakens. Therefore, the two-country assumption may not necessarily exaggerate the role of US joint ventures in Chinese growth.

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 1997, until it converges to the balanced growth path. There are no JVs in 1997. Calibrating along the transition is important in our 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 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 β is set to 0.4 based on the 1997 US Benchmark input-output table. The exit rate of JVs χ is set to 0.08, based on the average exit rate of Chinese firms reported by Chen et al. (2023).

Table 3: 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)
β	0.40	Tradable consumption share	1997 US Benchmark IO table
χ	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
κ, ξ	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			
ρ	0.03	Time preference	Literature
σ	4	Elast. of subst.	Broda and Weinstein (2006)
γ	2	Innovation/JV cost curvature	Acemoglu et al. (2018)
τ^x	2.85	Iceberg trade cost	Bai et al. (2024)
Internally calibrated by SMM			
α_{Hr}	0.60	US R&D cost scale parameter	Avg. R&D / sales of US firms
α_{Fr}	0.80	CN R&D cost scale parameter	Long-run avg. gap= 0
α_{Hd}	1.39	US JV scale parameter	Avg. JV sales shares
λ	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
δ^F	0.024	Prob. of exo. knowl. diffusion within country	2020 mfg. value added / emp. US/CN ratio
ψ	0.25	Leader & JV demand shifter	Mfg. US Compustat firm sales / gross output
ϕ	0.13	Prob. of direct knowl. diffusion	Direct effect on Chinese parents, Fig. 1
τ^z	1.84	JV iceberg technology cost	Sectoral regression results in US, Table 2
δ^D	0.029	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.

The JV profit share κ 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 $M_m(\boldsymbol{\Theta})$ 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 α_{Hr} is calibrated to match the average R&D-to-sales ratio for Compustat manufacturing firms. China's α_{Fr} is calibrated to match both countries to have the same average productivity level in the balanced growth path.[22] The JV cost scale parameter α_{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 λ governs long-run growth rate, we calibrate λ to match the US long-run GDP growth rate (2011-2019).

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

We pin down the direct diffusion parameter ϕ, the within-country diffusion parameter δ^D, and the JV iceberg technology cost τ^z using the facts 1, 2, and 3, respectively. The detailed procedure is outlined in Appendix D.1. We calibrate ϕ 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.[23] Because δ^D governs within-country diffusion, it directly relates to the fact 2. Because τ^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 2.[24]

Table 3 summarizes the estimation results. The model moments closely match their data counterparts (Panel A of Table 4). We obtain $\mathcal{D} = 20.0$, implying that the productivity of US

[22] 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.

[23] 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 β gives the average of the post-event coefficients in equation (3.1), which gives the estimate of 0.20.

[24] The restriction to fringe firms is consistent with the FDI exposure which excludes own JV affiliates.

Table 4: 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, Table 2)	−0.121	−0.111
CN indirect effects of JV on sales (col 1, Panel A, Table 1)	0.083	0.090
Direct effect on CN partners (Panel A, Figure 1)	0.203	0.200
Avg. US GDP per capita growth, 2011–2019	0.017	0.017
Avg. R&D-to-sales ratio, Compustat mfg. firms	0.075	0.073
JV sales shares in CN	0.125	0.110
Mfg. value added per emp. ratio (CN / US), 1999	0.084	0.084
Mfg. value added per emp. ratio (CN / US), 2020	0.382	0.382
Leader firms' sales share	0.277	0.280
Long-run avg. productivity ratio	1.001	1.000
Panel B. Non-Targeted Moments		
Sectoral regression, JV exposure & initial gap	0.104	0.169
US indirect effects of JV on R&D (col. 11, Panel A, Table 2)	−0.201	−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.

firms is roughly 9.6 times larger initially than Chinese firms on average. We obtain $\phi = 0.13$ and $\delta^F = 0.024$, implying that having JV increases the diffusion intensity from 2.4% to 15.4%. $\tau^z = 1.84$ suggests that JV's productivity is 46% lower than their US leaders.

The model also matches two non-targeted moments. First, it predicts a positive relationship between the initial US-China gap and sectoral JV exposure: larger gaps make JV more attractive because they generate larger total surplus (via higher JV profits and larger 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 (col. 11, Table 2).

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

Table 5: Baseline vs. Counterfactual Scenarios: Welfare Effects (%)

JV restriction	in 1999	in 1999 coordinated JV	in 1999 technology gap ≥ 6	in 2025
	(1)	(2)	(3)	(4)
US	1.20	−0.60	1.33	−0.67
China	−10.25	−1.99	−10.26	−2.49

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 6 (i.e., $m^F \geq 6$), and restricting JVs in 2025 (measured in 2025; column 4).

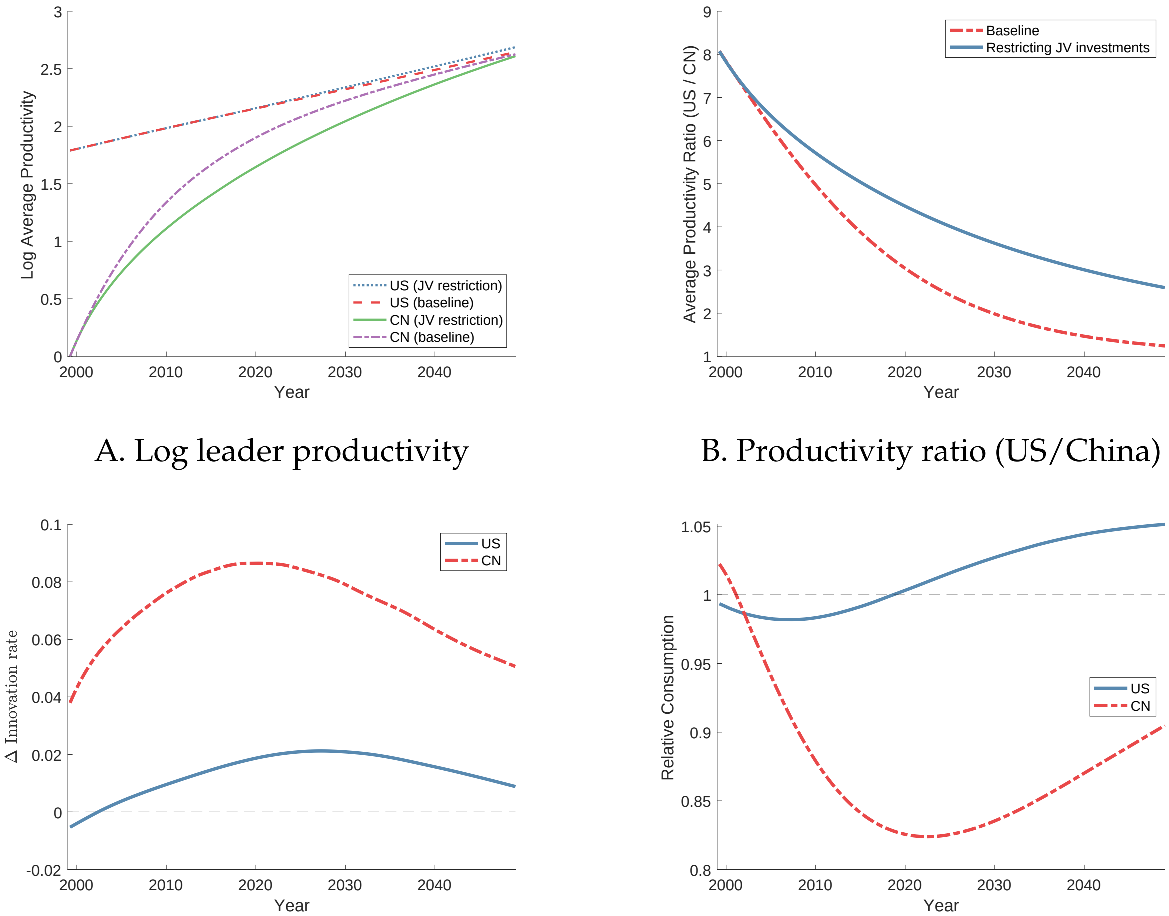
the US government restricts JV investment since 1999, and compare its welfare to the baseline scenario with JVs. In this counterfactual, firms are no longer allowed to establish new JVs, while existing JVs remain in place until they exit exogenously. We assume that this policy change is an unanticipated shock to all the agents.

Table 5 reports the welfare effects in consumption-equivalent variation. The JV restriction improves US welfare by 1.2% but reduces China's welfare by 10.3%.[25] In the counterfactual, the US-China technology gap widens and China's speed of convergence slows down (Panels A and B of Figure 2) because 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

[25]We can also define global welfare as a weighted average of lifetime utility, $W = \Lambda U^{US} + (1 - \Lambda) U^{CN}$. Then, JV restriction decreases global welfare as long as Λ, the welfare weight placed on the US, is less than 0.89.

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.

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). This is because, even though JVs enlarge market size and raise marginal returns to R&D, they also accelerate spillovers to Chinese rivals, eroding future profits and thus dampening the returns to innovation (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.[26] In our calibration, the competition effect dominates the market size benefits; as JVs are established in more products, the overall mix shifts toward those with lower innovation rates.[27] Consequently, over the medium term, the competition-driven composition effect dominates the option-value effect, leading to higher average innovation rates under the JV restriction.

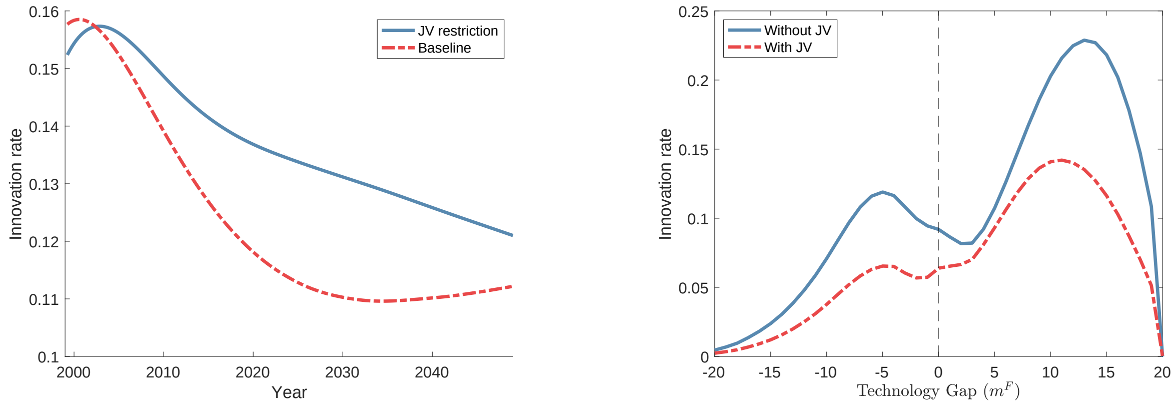
Next, we decompose the welfare effects of restricting JVs by income sources, as shown in Table 6. Here, real income is the sum of discounted leader profits (own profits + JV profits + JV fees), fringe profits, and labor income, all normalized by each country's real income in the baseline scenario. For the US, leader profits fall in the counterfactual because JV profits vanish and 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 weakens competitive pressure 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, both leader and fringe profits decline in China because of reduced diffusion, and labor income also falls as labor demand weakens. At the same time, slower diffusion pushes price levels higher.

To further examine the mechanism behind the welfare results and robustness of the results, we consider alternative modeling assumptions, reported in Table 7. When we shut

[26] 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. The asymmetry between the peaks (−5 vs. 13) reflects China's lower wages. When $m^F \approx 13$, US leaders are neck-and-neck in China, so they increase R&D to expand abroad. 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.

[27] In Appendix Figure D1, 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 $m^{DF} = m^{DH} = \bar{m}$.

down innovation channel, achieved by setting R&D cost parameter values to infinity, the JV restriction still increases US welfare by 0.39%, although the magnitude decreases by 68% (0.39% vs. 1.20%). 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 0.73%. 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 (ϕ, δ^F, δ^D, $\mathcal{D}$, and κ), reported in Appendix Table D1.

Another important question is how the quid pro quo policy, which mandates direct technology transfer through JVs, affects US and Chinese welfare. In an alternative counterfactual, we set $\phi = 0$, allowing US leaders to form JVs with Chinese leaders without any direct technology transfer. This setup resembles FDI through wholly owned foreign enterprises. In this scenario, US welfare increases by 3.2%, while Chinese welfare declines by 5.3%. These

Table 6: Baseline vs. Restricting Joint Venture Investments in 1999: Net Present Value of Real Profits and Labor Income

	Baseline	Shutting down JV	Changes (%)
US leader profit (own + JV + JV fee)	0.047	0.037	−22.13
Own profit	0.034	0.037	7.42
JV profit	0.008	0.000	n/a
JV fee revenue	0.005	0.000	n/a
US fringe profit	0.065	0.068	4.87
US labor income	0.888	0.914	2.94
US total real income	1.000	1.019	1.88
CN leader profit (own + JV + JV fee)	0.042	0.038	−10.43
Own profit	0.041	0.037	−8.77
JV profit	0.005	0.000	n/a
JV fee payment	−0.004	0.000	n/a
CN fringe profit	0.063	0.060	−5.11
CN labor income	0.895	0.817	−8.71
CN total real income	1.000	0.914	−8.55

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.

Table 7: Robustness. Baseline vs. Restricting Joint Venture in 1999. Alternative Assumptions

	Δ US Welfare (%)	ΔCN Welfare (%)	Δ US Innovation rate (%)	Δ CN Innovation rate (%)
Baseline	1.20	−10.25	1.36	7.13
No innovation	0.39	−17.05	0	0
Love of variety	0.73	−10.58	1.36	7.13
Constant markup	1.46	−8.25	1.30	4.98

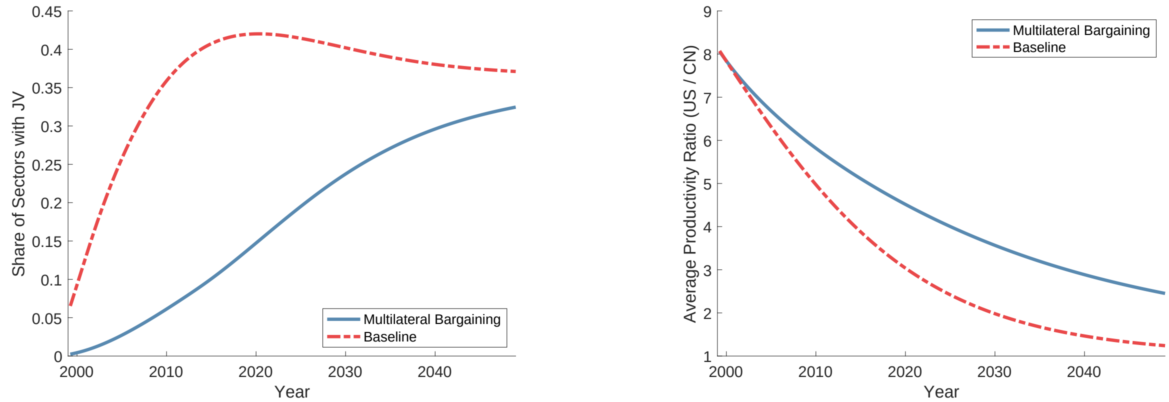
Notes. This table reports the effects of restricting JV in 1999 with alternative parameterizations. Δ Welfare is expressed in consumption-equivalent units, and Δ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

welfare results are consistent with Holmes et al. (2015), who also find that the quid pro quo policy benefits Chinese welfare, while negatively affects US welfare.

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

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.

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 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 $C^E = -\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})$.

Coordinated JV raises US welfare by 1.7% relative to the uncoordinated baseline, exceeding the welfare gain from restricting JV investments in the baseline case. Furthermore, 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 2.0%, compared to the case without JV restriction (col. 2 of Table 5). 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.

6.3 Comparative Advantage and Joint Venture Restriction 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 4), 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. As a result, diffusion from JVs biases China's productivity growth toward sectors in which the US initially holds a comparative advantage. Well-known theoretical results (Dornbusch et al., 1977; Samuelson, 2004) show that the welfare gains from trade can decline when China becomes similar with the US in terms of relative productivity.[28] To explore this, we first compare gains from trade in the baseline and the counterfactual with the JV restriction. In particular, we compare the welfare with and without trade, holding productivity and other equilibrium objects constant. Consistent with the theoretical results, US gains from trade is 3.9% in the baseline and rises to 4.2% in the counterfactual.

Next, we simulate a state-dependent restriction that bans JVs only when the productivity gap is large to limit excessive diffusion to sectors that US has a comparative advantage. Specifically, JVs are banned when $m^F \geq 6$ (i.e., US leaders are at least 6 steps ahead). We select the threshold of 6 because it gives the largest welfare gains. The policy can be viewed as an effort to maintain US comparative advantage in high-tech sectors. Under this policy,

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

US welfare rises by 1.33% relative to the baseline, which means that it is preferable to the total ban of JVs (col. 3 of Table 5). However, this policy has an unintended consequence of weakening US leaders' innovation incentives as it reduces their value of maintaining $m^F \geq 6$.

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 5; measured in 2025) by 0.7%, flipping the sign. By then, the US-China technology gap becomes much smaller (Appendix Figure D3), so diffusion and the resulting negative externality is 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 D2), suggesting that the policy's impact depends on the 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.

The model abstracts from formal licensing contracts (Santacreu, 2024), which represent another important channel of cross-country knowledge diffusion. While the underlying economic mechanisms of JVs and formal licensing may be similar, quantitatively assessing the roles of both channels presents a promising direction for future research.

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, 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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Supplemental Appendix

A. Appendix: Data

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 B5—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. 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.

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.

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.

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 $\text{Total sales}_{j,98}^{\text{CN}} = \sum_{h \in \text{CIC}(j)} \omega_h^j \sum_{g \in \mathcal{F}_{h,98}} \text{Sale}_{gh,98}$, 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 ω_h^j is a weight of CIC h assigned for SIC j. The numerator $\Delta\text{FDI sales}_j$ is computed similarly for FDI affiliates: $\Delta\text{FDI sales}_j = \sum_{h \in \text{CIC}(j)} \omega_h^j \sum_{g \in \mathcal{J}_{h,12}} \text{Sale}_{gh,12} - \sum_{h \in \text{CIC}(j)} \omega_h^j \sum_{g \in \mathcal{J}_{h,99}} \text{Sale}_{gh,99}$, where $\mathcal{J}_{ht}$ is a set of FDI affiliates with CIC h code in year t. For the regression models in Table (2), 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: $\Delta\text{FDI}_h = \sum_{j \in \text{SIC}(h)} \omega_j^h \Delta\text{FDI sales}_j$, where ω_j^h is a weight of SIC j assigned for CIC h that are mapped to multiple 4-digit SIC codes.

B.2 Facts 2 and 3: Instrumental Variable Strategy

The OLS estimates can be biased due to endogeneity as unobservable factors may affect both FDI flows and firm growth. We propose two IV strategies to alleviate this concern.

First IV Strategy. First, we construct the IV 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:

$$\text{IV}_j^{\text{JP-SK}} = \frac{\Delta\text{India FDI (Japan \& S. Korea) sales}_{jt}}{\text{Total sales}_{j,98}^{\text{CN}}} = \frac{\sum_{g \in \mathcal{J}_{j,12}^{\text{IN,JP-KR}}} \text{Sale}_{gj,12} - \sum_{g \in \mathcal{J}_{j,99}^{\text{IN,JP-KR}}} \text{Sale}_{gj,99}}{\text{Total sales}_{j,98}^{\text{CN}}}, \tag{B.1}$$

$\mathcal{J}_{jt}^{\text{IN,JP-KR}}$ 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, typically larger than domestic Indian firms.

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, and Japan and South Korea because they were the two largest sources of FDI in China.

Second IV Strategy. We also consider the second IV strategy, where we instrument the FDI exposure with domestic Chinese FDI policy change based on the Catalogue. Lu et al. (2017)

Threats to identification. Regarding the first IV, there can be two main potential threats to identification: export platform and technological changes. 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 or reduce communication costs between headquarters and affiliates. These shocks may make certain sectors more attractive for FDI, potentially correlating FDI by MNEs in the US, Japan, or South Korea. Technological changes can also be a threat for the second IV if such changes have influenced the Chinese government's decision to liberalize FDI in particular sectors.

We investigate these concerns by inspecting pre-trends and industry-level balance, following Borusyak et al. (2022), reported in Appendix Table B7. First, pre-1999 5 year growth (1993-1998) is 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 B8).[29]

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

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

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 IVs: 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.

Estimation results. Table B9 reports the results. The IV estimates are qualitatively similar to the OLS estimates but larger in magnitude. The IVs are strong, except for the second IV in the case of Chinese positive spillovers. The results remain robust to the additional controls related to technological trends.

B.3 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:

$$y_{imt} = \sum_{\tau=-5}^{5} \beta_\tau \big(D^{\tau}_{mt} \times \mathbb{1}[\text{JV Formation}_{imt}] \big) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}, \tag{B.2}$$

where $\mathbb{1}[\text{JV Formation}_{imt}]$ is a dummy of treatment, and D^{τ}_{mt} are event study variables. δ_{im} and δ_{mt} are firm-pair and pair-year fixed effects. Standard errors are clustered at the pair level. The dependent variables are dummies of receiving 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 diffused 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.

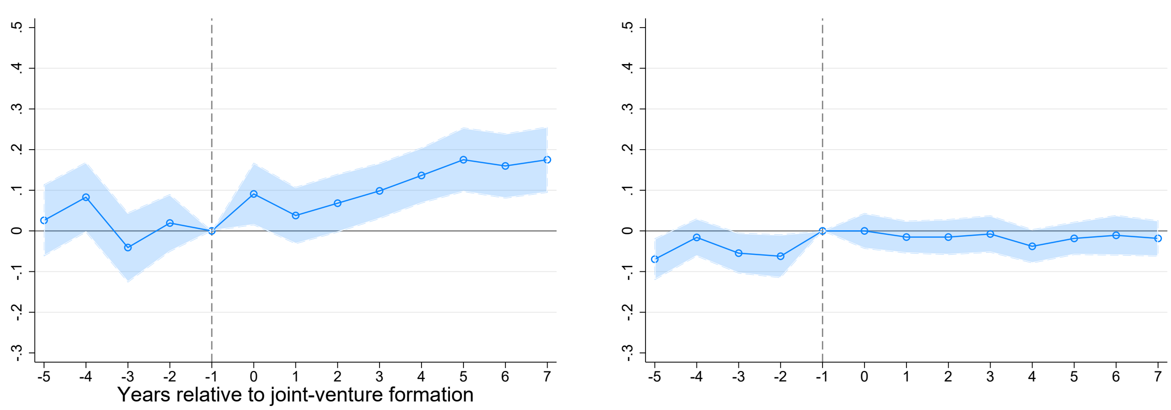
B.4 Additional Figures and Tables

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.

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.2). 95% confidence intervals, based on standard errors clustered at the pair levels, are reported. β_{-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.

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.

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). β_{-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.

Table B4: OLS. Quality Upgrading of Chinese Firms

Dep. var.	Δ # export prod	Δ # export cty	Δ # import prod	Δ # import cty	ΔWage per emp	Dum gvnt high-tech
	(1)	(2)	(3)	(4)	(5)	(6)
ΔFDI_{fj}	17.75***	15.18***	6.27**	8.65***	2.46***	3.54***
	(4.18)	(3.54)	(2.48)	(2.48)	(0.72)	(0.73)
NTRgap_j	1.47***	1.18***	1.75***	1.68***	0.02	0.10
	(0.42)	(0.41)	(0.38)	(0.40)	(0.15)	(0.11)
Mean dep. var.	36.30	33.77	−24.95	−7.21	120.54	18.97
# clusters	153	153	154	154	157	157
N	7316	7312	6414	6410	14817	14844

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 estimates of equation (3.3). ΔFDI_{fj} is defined in equation (3.4). In columns 1-6, the dependent variables are the DHS growth of the numbers of exporting/importing products/countries between 2000-2013, the DHS growth of wages per employment, and dummies for firms receiving high-tech status from the government in 2024. 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. All regression models are weighted by initial sales.

Table B5: Robustness. OLS. Negative Competition Effects to Global Firms

Dep. var.	ΔSale	ΔEmp	ΔCapital	ΔR&D
	(1)	(2)	(3)	(4)
ΔFDI_{fj}	−6.65**	0.38	−5.60**	−9.99***
	(2.87)	(1.43)	(2.16)	(3.59)
NTRgap_j	−0.87	−0.54	−0.75	−0.05
	(0.70)	(0.41)	(0.52)	(0.90)
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 estimates of equation (3.3). Estimation samples include global firms, excluding those from China, India, South Korea, and US. The FDI exposure ΔFDI_{fj} is defined in equation (3.4). In columns 1-2, 3-4, and 5-6, the dependent variables are DHS growth rates of sales, employment, capital, and R&D expenditures 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. All regression models are weighted by initial sales.

Table B6: Robustness. OLS. Positive Spillovers to Chinese Firms and Negative Competition Effects to US Firms

Robustness	Chinese firms: Positive spillovers				US firms: Negative competition			
	Alt. sample ex. FDI subsidiaries	Alt. clustering 4-digit level	Alt. sample period 1999-2007	Alt. weight emp.	Alt. sample ex. FDI subsidiaries	Alt. clustering 4-digit level	Alt. sample period 1999-2007	Alt. weight emp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Dependent variable: $\Delta Sale$								
ΔFDI_{fj}	9.08***	8.97***	15.80***	8.54***	−10.10***	−11.08***	−9.39	−9.11***
	(3.15)	(1.67)	(5.03)	(1.84)	(2.86)	(2.72)	(6.25)	(2.40)
Mean dep. var.	81.74	79.61	47.49	84.04	7.84	8.69	14.77	8.88
Panel B. Dependent variable: ΔEmp								
ΔFDI_{fj}	5.81***	7.30***	12.94***	6.11***	−9.78***	−10.65***	−11.43**	−7.86***
	(1.87)	(1.65)	(3.21)	(1.29)	(3.38)	(3.00)	(4.97)	(2.75)
Mean dep. var.	−18.92	−7.08	−6.30	−39.96	−11.27	−10.82	−3.32	−13.46
NTR gap ctrl.	✓	✓	✓	✓	✓	✓	✓	
# clusters	156	380	157	157	105	173	110	105
N	11978	14844	22529	14834	949	1017	1437	1017

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 OLS estimates of equation (3.3). ΔFDI_{fj} is defined in equation (3.4). In Panels A and B, the dependent variables are the DHS growth rates of sales and employment for Chinese firms. Columns 1 excludes all FDI subsidiaries (JV and WOFE) among Chinese firms and column 5 excludes all firms that formed FDI in China among US firms. Columns 2 and 6 consider alternative clustering at the CIC 4-digit level. Columns 3 and 7 consider an alternative sample period of 1999-2007. Columns 4 and 8 consider an alternative weights based on employment. Columns 1-4 include dummies of state-owned firms and FDI affiliates, and province fixed effects. Except for columns 4 and 8, regression models are weighted by initial sales.

Table B7: Pre-trend and Shock Balance Test of the IV

Balance variable	$IV_j^{JP,SK}$			IV_j^{pol}		
	Coef.	SE	p-val.	Coef.	SE	p-val.
Panel A. Pre-trend						
Δ Log gross output, 1993-1998	0.11	(0.06)	[0.06]	−0.22	(0.19)	[0.24]
Δ Log emp., 1993-1998	0.10	(0.06)	[0.10]	−0.22	(0.19)	[0.25]
Δ Log PPI, 1993-1998	0.05	(0.05)	[0.35]	−0.02	(0.06)	[0.77]
Δ US import (ex. CN, IN, JP, SK) / absorption, 1996-1998	0.04	(0.02)	[0.12]	−0.01	(0.03)	[0.69]
Δ US-CN import / absorption, 1996-1998	−0.05	(0.06)	[0.41]	−0.04	(0.08)	[0.65]
Panel B. Industry-level balance						
US-CN import / absorption 1996	−0.06	(0.04)	[0.14]	0.00	(0.06)	[0.95]
US-IN import / absorption 1996	−0.01	(0.01)	[0.28]	0.02	(0.02)	[0.33]
CN-IN import / absorption 1996	−0.02	(0.01)	[0.15]	0.05	(0.02)	[0.01]
IN-CN import / absorption 1996	−0.02	(0.02)	[0.24]	0.02	(0.02)	[0.24]
JV sales share 1998	−0.04	(0.04)	[0.28]	−0.12	(0.16)	[0.45]
Number of JV firms to total number of firms ratio 1998	0.02	(0.01)	[0.12]	0.00	(0.02)	[0.99]
US import (ex. CN, IN, JP, SK) / absorption 1996	0.14	(0.04)	[0.00]	−0.12	(0.06)	[0.05]
Ratio of capital to wage-bills 1993	0.01	(0.07)	[0.91]	0.03	(0.11)	[0.81]
Ratio of wage bills to value-added 1993	0.03	(0.05)	[0.56]	−0.07	(0.09)	[0.47]
R&D intensity 1993	0.08	(0.11)	[0.47]	0.05	(0.06)	[0.37]
Production workers' share of employment 1993	0.27	(0.06)	[0.00]	−0.28	(0.13)	[0.03]
High-tech investment shares 1990	−0.13	(0.09)	[0.15]	0.06	(0.13)	[0.62]
Computer investment shares 1990	−0.18	(0.05)	[0.00]	0.17	(0.14)	[0.22]
N		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 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 R&D-to-sales ratios, calculated from Compustat. Columns 1-3 and 4-6 use IVs based on South Korea and Japan's FDI in India and on changes in China's domestic FDI policy, respectively. 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 B8: Firm-level Pre-trend. Correlations between the IV and Pre-1999 Firm Size Growth

	US firms DHS growth, 1993-1998			
Dep. var.	ΔSale (1)	ΔEmp. (2)	ΔCapital (3)	ΔExport (4)
	Panel A. IV based on S. Korea & Japan's FDI in India			
$IV_j^{JP\text{-}SK}$	−2.51	−0.68	18.31	−19.20
	(17.45)	(23.08)	(12.88)	(35.88)
	Panel B. IV based on China FDI policy change			
IV_j^{pol}	3.01	2.44	−1.39	−1.40
	(4.66)	(4.96)	(3.56)	(7.03)
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. Panels A and B use IVs based on South Korea and Japan's FDI in India and on changes in China's domestic FDI policy, respectively. 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 B9: Robustness. IV. Positive Spillovers to Chinese Firms and Negative Competition Effects to US Firms

Dep. var.	Chinese firms: Spillovers				US firms: Competition			
	ΔSale		ΔEmp		ΔSale		ΔEmp	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. IV based on S. Korea & Japan's FDI in India							
ΔFDI_{fj}	12.76***	10.92***	10.01***	11.00***	−17.36***	−16.11***	−18.32***	−14.61***
	(3.37)	(2.98)	(2.44)	(2.14)	(3.74)	(3.81)	(4.33)	(3.87)
NTRgap_j	0.11	0.38	0.62*	0.79***	−1.63*	−1.72**	−1.58	−1.74**
	(0.32)	(0.34)	(0.32)	(0.28)	(0.93)	(0.77)	(1.04)	(0.77)
KP-F	45.82	42.73	45.82	42.73	130.64	134.08	130.64	134.08
	Panel B. IV based on China's FDI policy change							
ΔFDI_{fj}	15.02**	19.05**	2.15	4.58	−28.17***	−33.18***	−32.13***	−34.90***
	(6.22)	(7.44)	(8.96)	(8.94)	(8.91)	(9.96)	(10.89)	(10.58)
NTRgap_j	0.20	0.72	0.33	0.52	−2.48**	−2.78***	−2.66*	−3.00***
	(0.46)	(0.47)	(0.44)	(0.43)	(1.17)	(0.99)	(1.36)	(1.03)
KP-F	3.37	5.58	3.37	5.58	13.42	16.62	13.42	16.62
Add. ctrl.		✓		✓		✓		✓
Mean dep. var.	79.61	79.61	−7.08	−7.08	8.69	8.69	−10.82	−10.82
# clusters	157	157	157	157	105	105	105	105
N	14844	14844	14844	14844	1017	1017	1017	1017

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 estimates of equation (3.3). ΔFDI_{fj} is defined in equations (3.4). 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. Panels A and B use IVs based on South Korea and Japan's FDI in India and on changes in China's domestic FDI policy, 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. 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.

C. Additional Mathematical Expressions

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

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

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

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

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 $m^F \leq 0$. A Home leader's value function with JV is

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

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

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

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

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:

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

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

Law of motion for gaps and JV status. The law of motion for $\mu_t(\mathbf{m};\mathcal{J})$ is

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

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. δ_i is firm time-invariant fixed effects, and δ_{jt} is product-year fixed effects. $\mathbb{1}[\text{Post-JV}_{it}]$ is a dummy which equals 1 after forming 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 Equation (3.3), with two key differences.

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

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

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 $m^F \in \{-\bar{m}, \dots, \bar{m}\}$ 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).

ΔJV_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.

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.

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

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

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

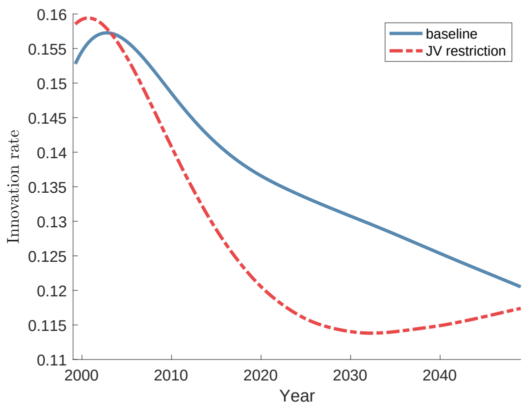
$$C = \frac{\xi^E(1-\xi)}{\xi^E(1-\xi)+\xi}\left\{\Delta^{\text{JV}} V_{ht}(\mathbf{m}) + \Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m})\right\} - \frac{\xi}{\xi^E(1-\xi)+\xi}\Delta^{\text{JV}} V_{ft}(\mathbf{m}) \tag{D.5}$$

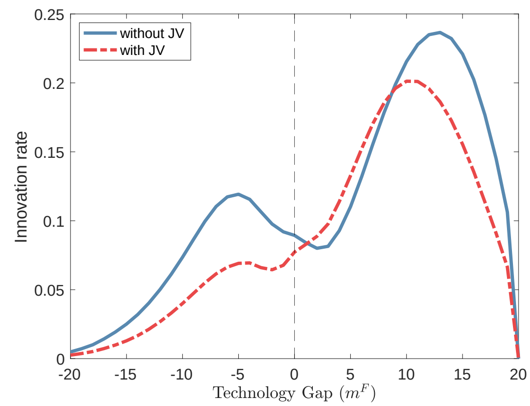
$$C^E = \frac{\xi(1-\xi^E)}{\xi(1-\xi^E)+\xi^E}\left\{\Delta^{\text{JV}} V_{ht}(\mathbf{m}) + \Delta^{\text{JV}} V_{ft}(\mathbf{m})\right\} - \frac{\xi^E}{\xi(1-\xi^E)+\xi^E}\Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m}). \tag{D.6}$$

When we set $\xi^E = 1$, the above expressions collapse to equation (6.1).

D.3 Additional Figures and Tables

Figure D1: US Innovation Rate over Time and Technology Gap. The Cases of Larger Market Size $\kappa = 1$ and No Direct Diffusion $\phi = 0$

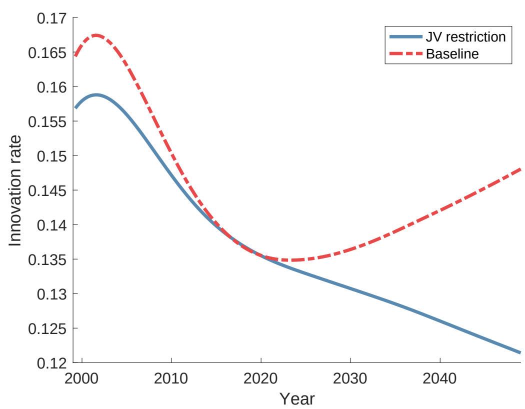


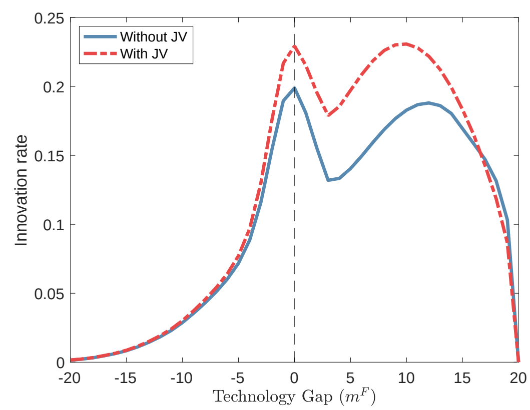


Larger market size effect ($\kappa = 1$)

A. US average innovation rate

B. US Innovation rate over technology gap





No direct diffusion ($\phi = 0$)

C. US average innovation rate

D. US Innovation rate over technology gap

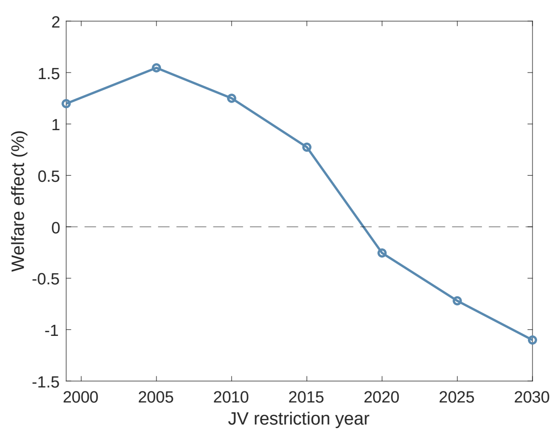
Notes. In Panels A and B, we consider the case of larger market size effects by setting $\kappa = 1$. In Panels C and D, we shut down direct diffusion by setting $\phi = 0$. Panels A and C plot the average innovation rate in baseline and counterfactual scenarios. Panels B and D plots the innovation rate 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 $m^{DF} = m^{DH} = \bar{m}$.

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	1.20	−10.25	1.36	7.13
	Panel B. Direct diffusion (baseline: $\phi = 0.13$)			
$\phi = 0.08$	0.87	−10.31	0.82	7.33
$\phi = 0.18$	1.27	−9.86	1.66	6.76
	Panel C. Across-country diffusion (baseline: $\delta^F = 0.024$)			
$\delta^F = 0.019$	0.88	−10.81	1.44	7.24
$\delta^F = 0.029$	1.28	−9.09	1.51	6.20
	Panel D. Within-country diffusion (baseline: $\delta^D = 0.027$)			
$\delta^D = 0.022$	1.31	−10.13	1.50	7.25
$\delta^D = 0.032$	1.10	−10.36	1.23	7.00
	Panel E. Initial technology gap (baseline: $\mathcal{D} = 20$)			
$\mathcal{D} = 23$	1.64	−9.32	1.53	7.15
$\mathcal{D} = 17$	0.77	−9.32	1.39	7.36
	Panel F. US JV profit share (baseline: $\kappa = 0.54$)			
$\kappa = 0.75$	0.86	−10.87	1.20	7.03
$\kappa = 0.25$	1.66	−9.25	1.57	7.19

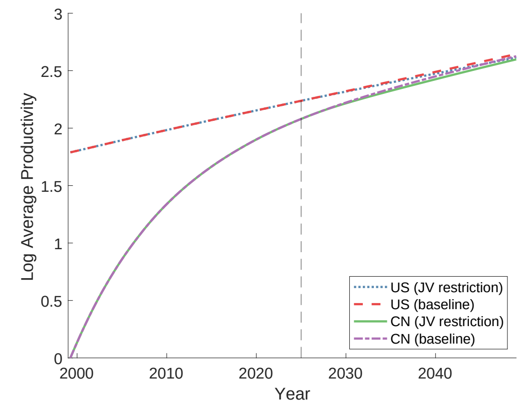
Notes. This table reports the effects of restricting JV in 1999 with alternative parameterizations. Δ Welfare is expressed in consumption-equivalent units, and Δ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

Figure D2: Baseline vs. Restricting Joint Venture Investments over Different Years. Welfare Effects (%)

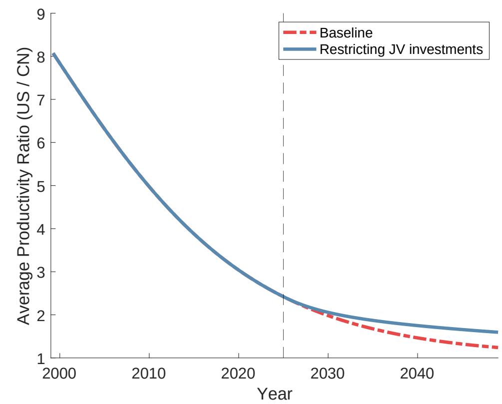


Notes. This figure reports consmption-equivalent welfare changes of the US from restricting JV investments in different years, compared to the baseline scenario. The x-axis denotes for years in which JV investments are restricted.

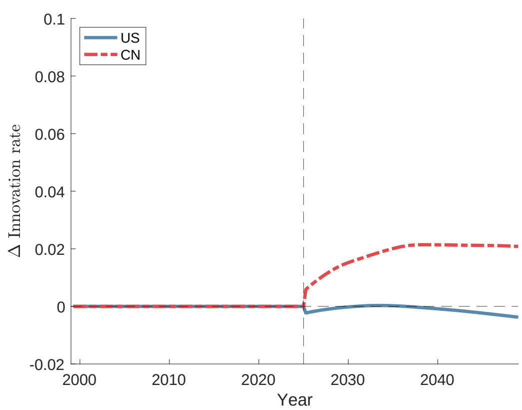
Figure D3: Baseline vs. Restricting Joint Venture Investments in 2025: Dynamics of Productivity, Innovation, and Consumption



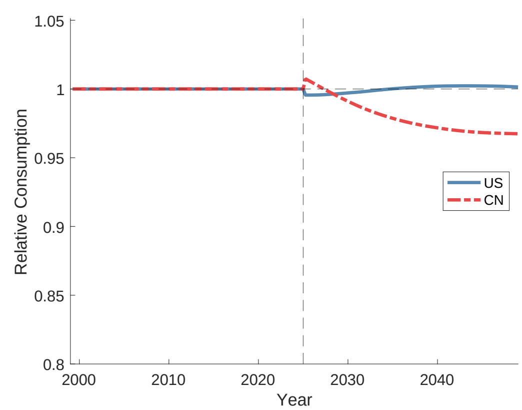
A. Log leader productivity



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.

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